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

University of Strathclyde Glasgow

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.

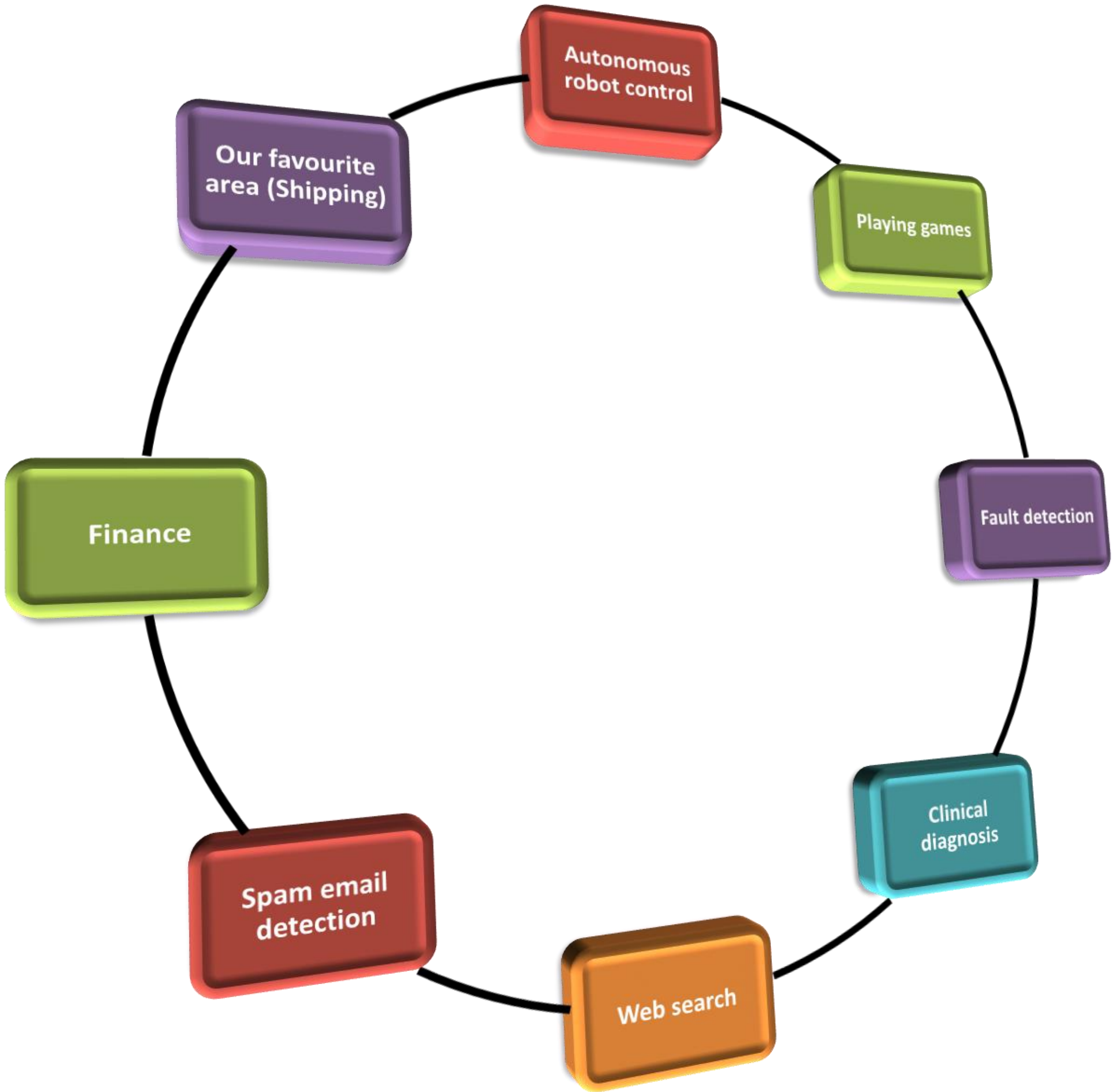
Statistics:

- Inference from a sample

Computer science:

- Efficient algorithms to solve the optimization problem
- Representing and evaluating the model for inference

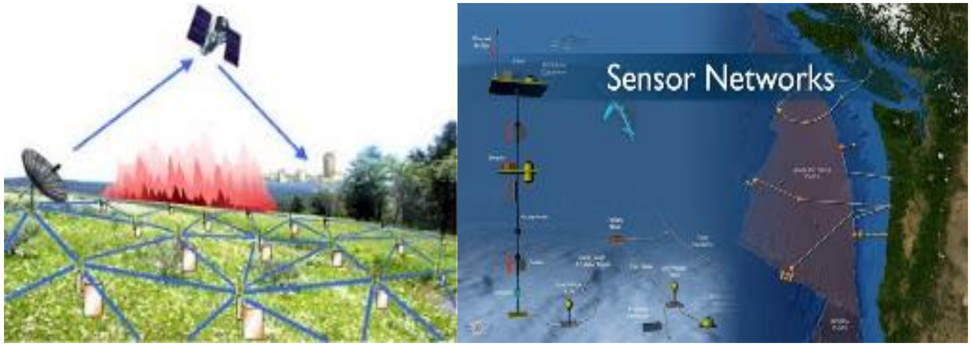
Introduction



Social media and networks

Mobile devices

Scientific instruments



Sensor technology and networks

Introduction

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Maersk

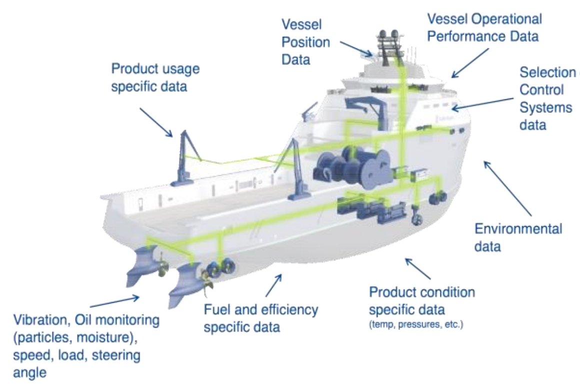
Neste

MARORKA

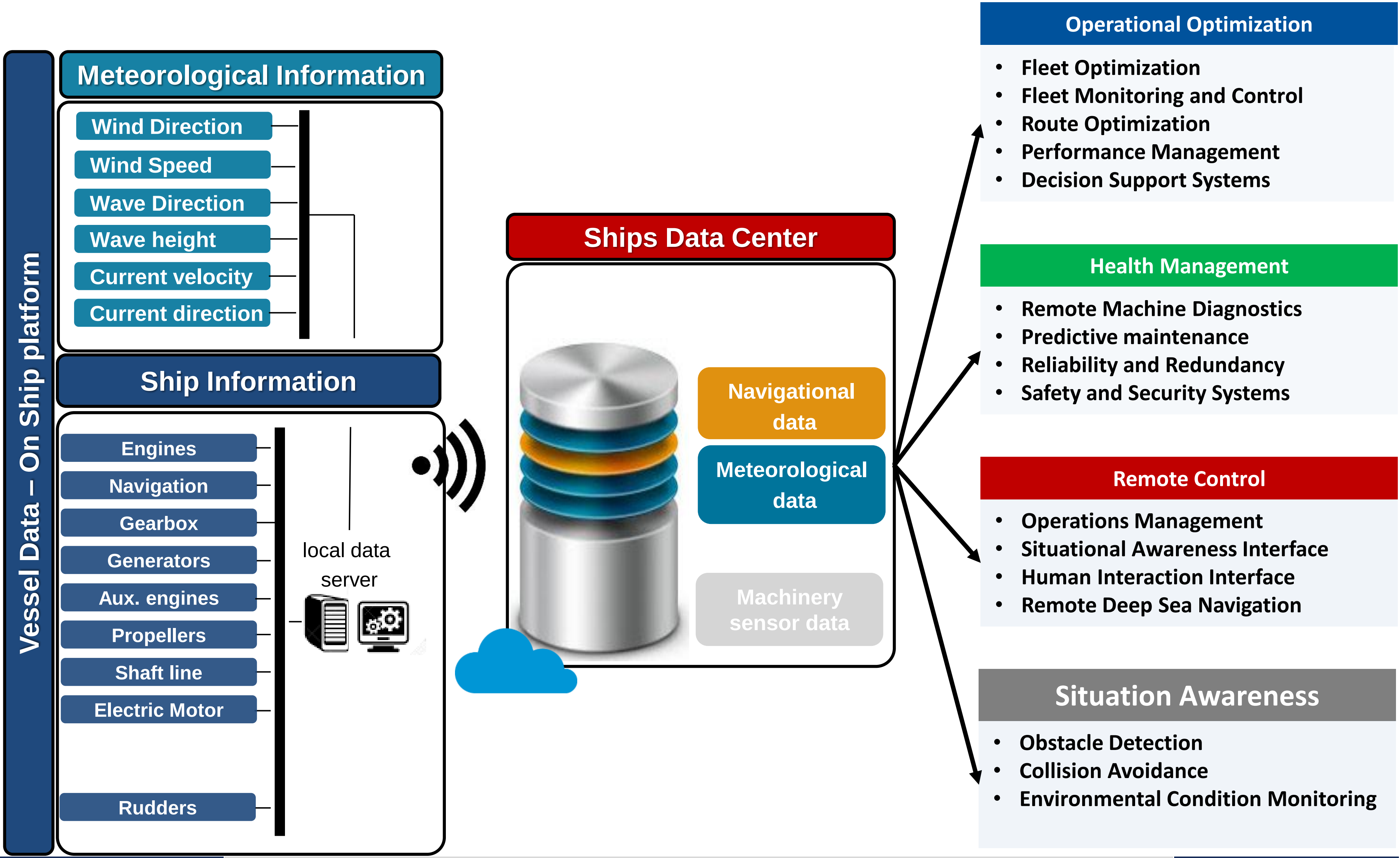
Cosco

Royston

ABS



Ships Data Center



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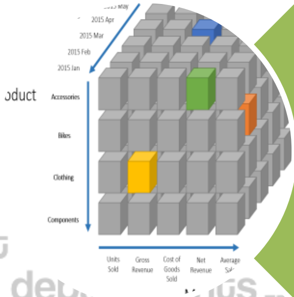
What to do with these data?



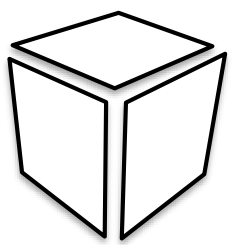
Aggregation and Statistics

Indexing, Searching, and Querying

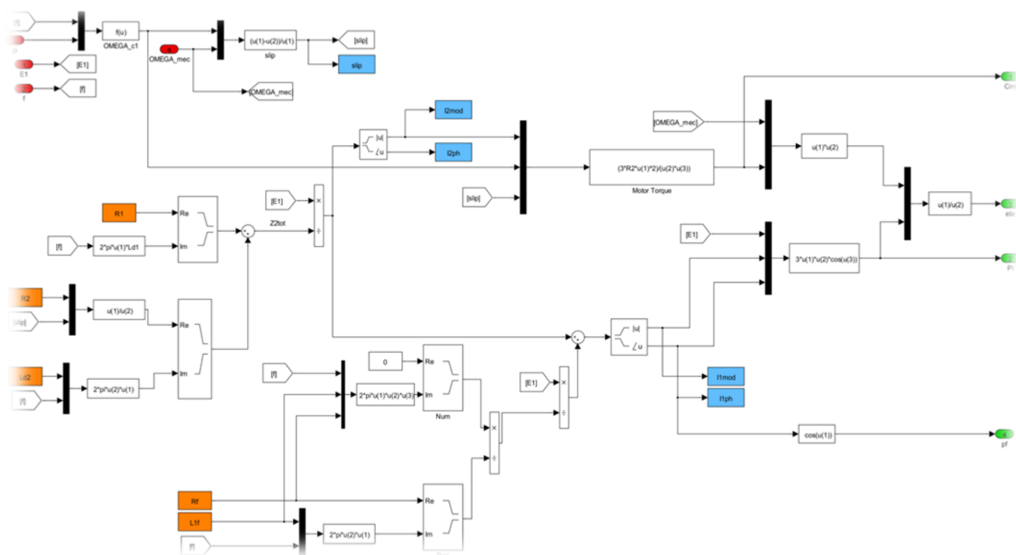
Knowledge discovery (Data Mining, Statistical Modeling)

Introduction

White, Black or Gray?

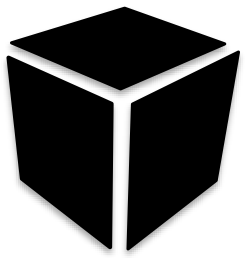


White Box Models are based on the knowledge of the physical underling processes.

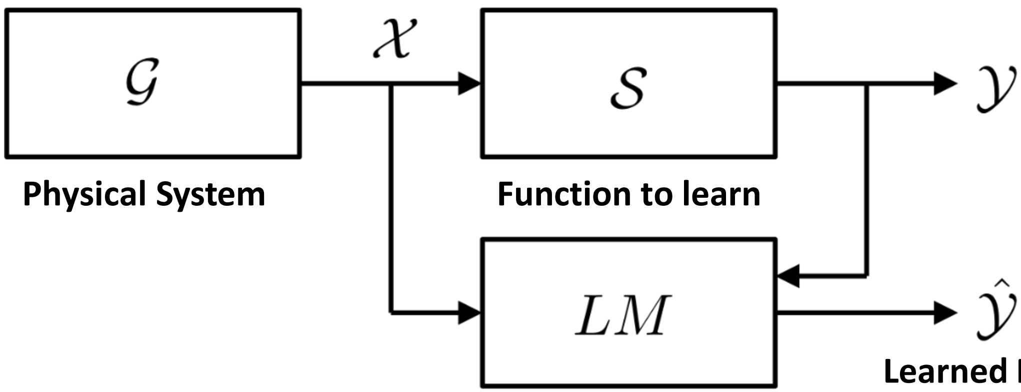


White, Black or Gray?

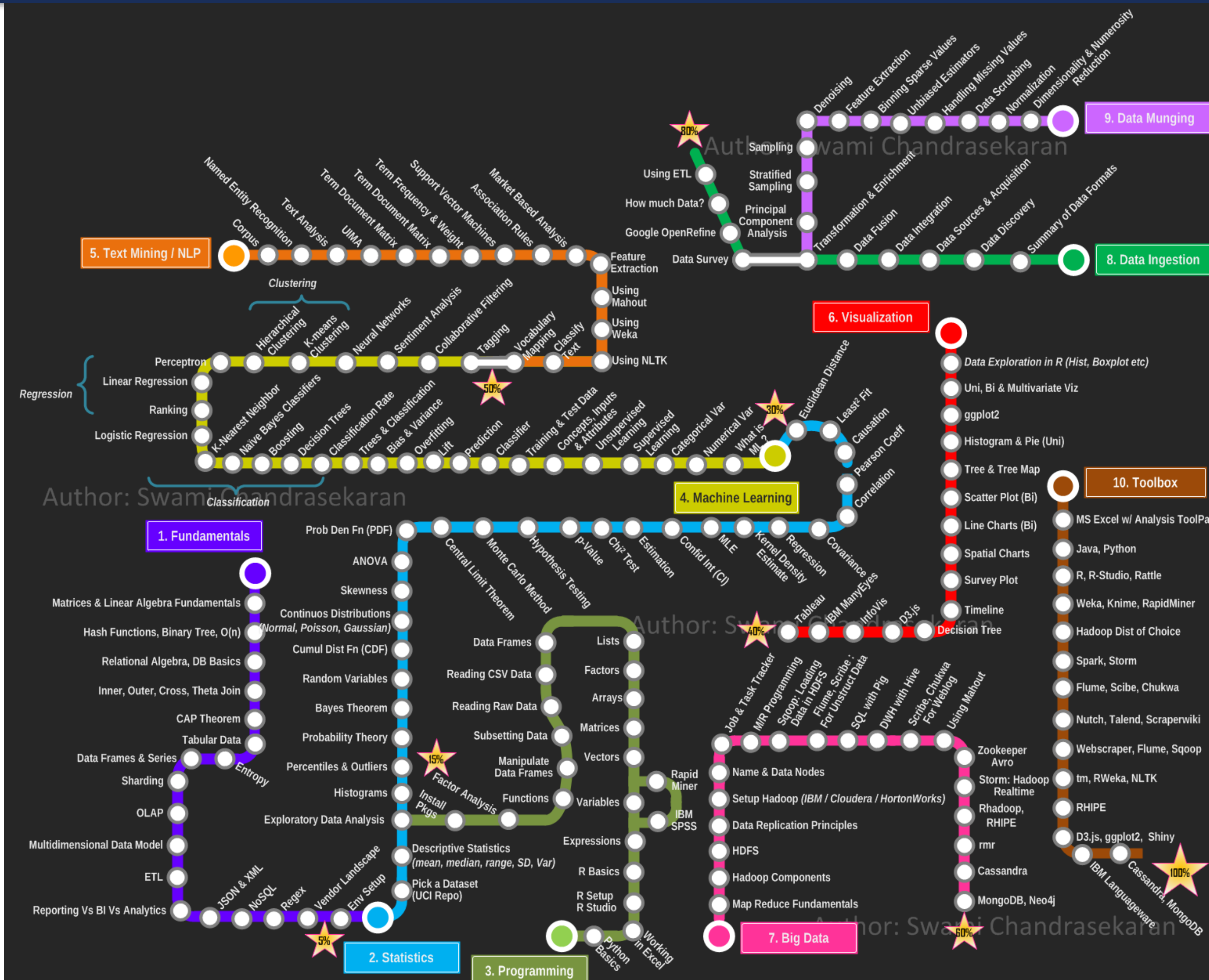
Physical problem not trivial to solve:
i.e. evaluate the system health status by means of field measurements



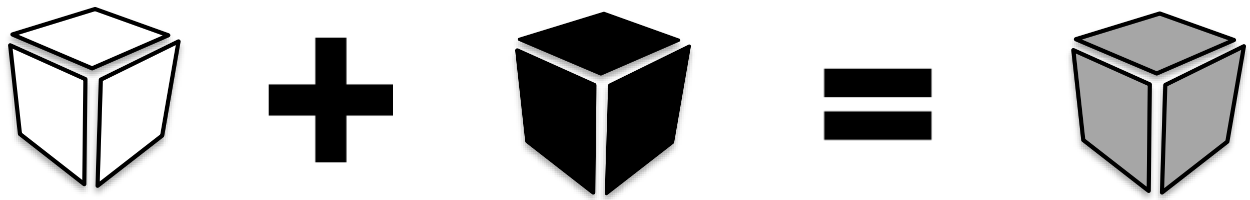
Black box learning system able to learn from the available observation (on board sensor measures) of the system.



Introduction



White, Black or Gray?



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

The White Box Approach

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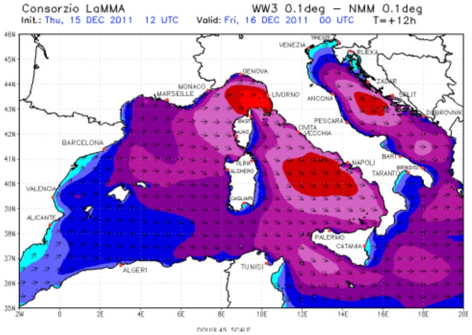
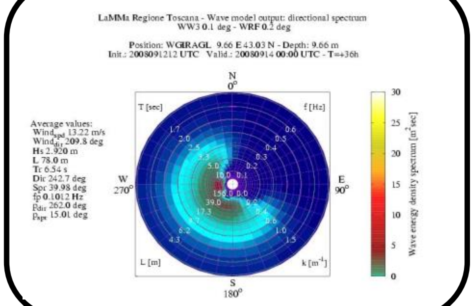
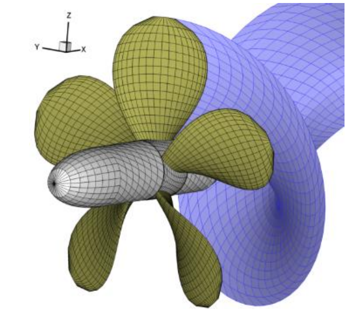
Wind Resistance



Waves Added Resistance



Propeller Performance

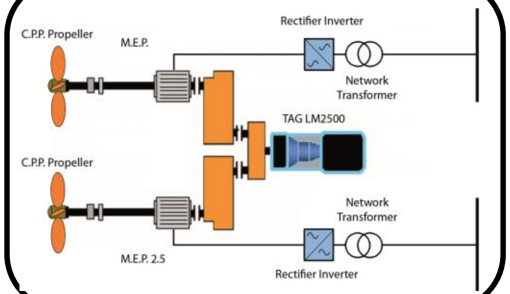


Fuel Consumption

Calm Water Hull Resistance

Trade/route

Propulsion Plant



The White Box Approach

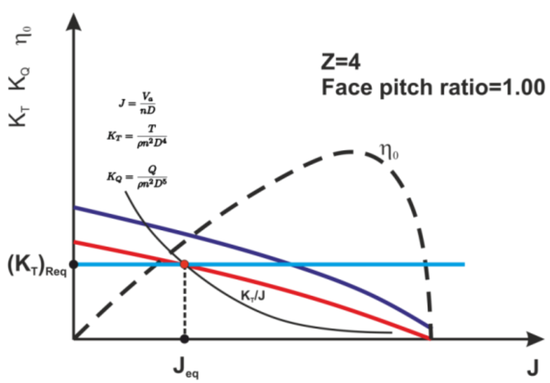
White Box Models describe the behaviour of the system based on governing physical laws of each components and taking into account their mutual interactions.

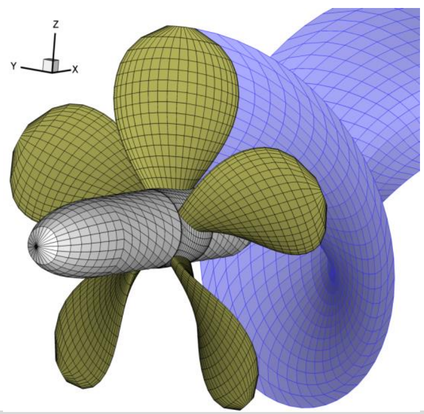
The higher the detail in the modelling of the physical equations which describe the different phenomena, the higher the expected **accuracy** of the results and the **computational time** required for the simulation.

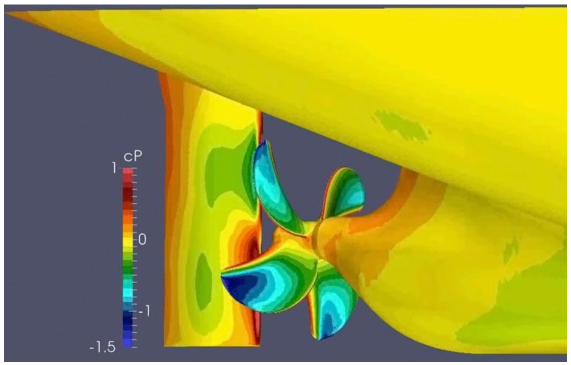
OPEN WATER | **PANEL METHOD** | **CFD**

Accuracy →

← **Computational Time**





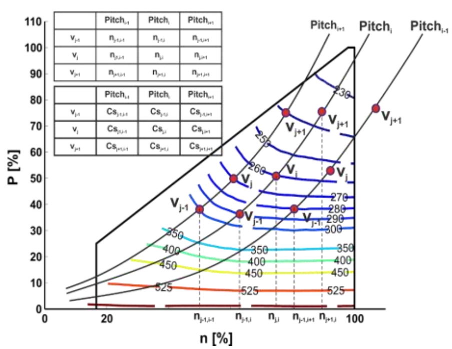


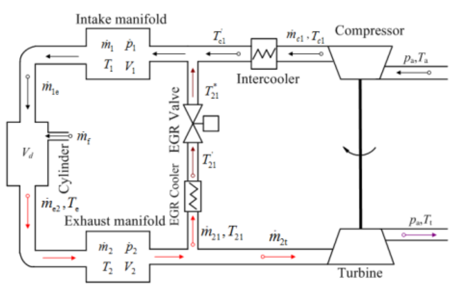
The White Box Approach

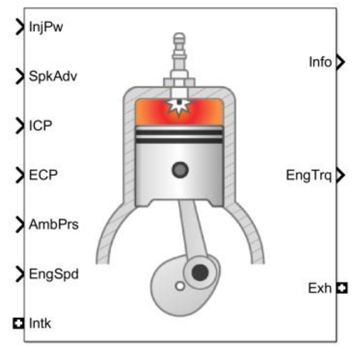
Look-up tables | **Mean Value Models** | **0D/1D Models** | **CFD**

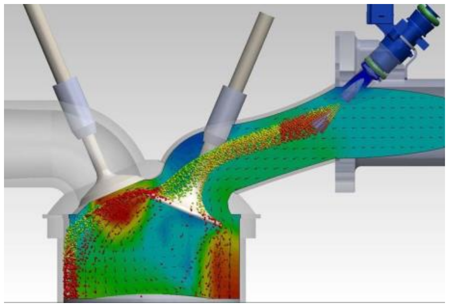
Accuracy →

← **Computational Time**

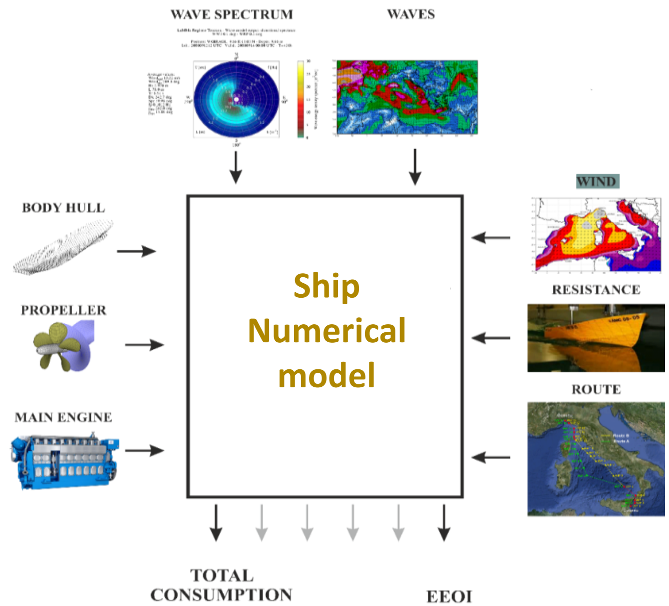








The White Box Approach



- 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

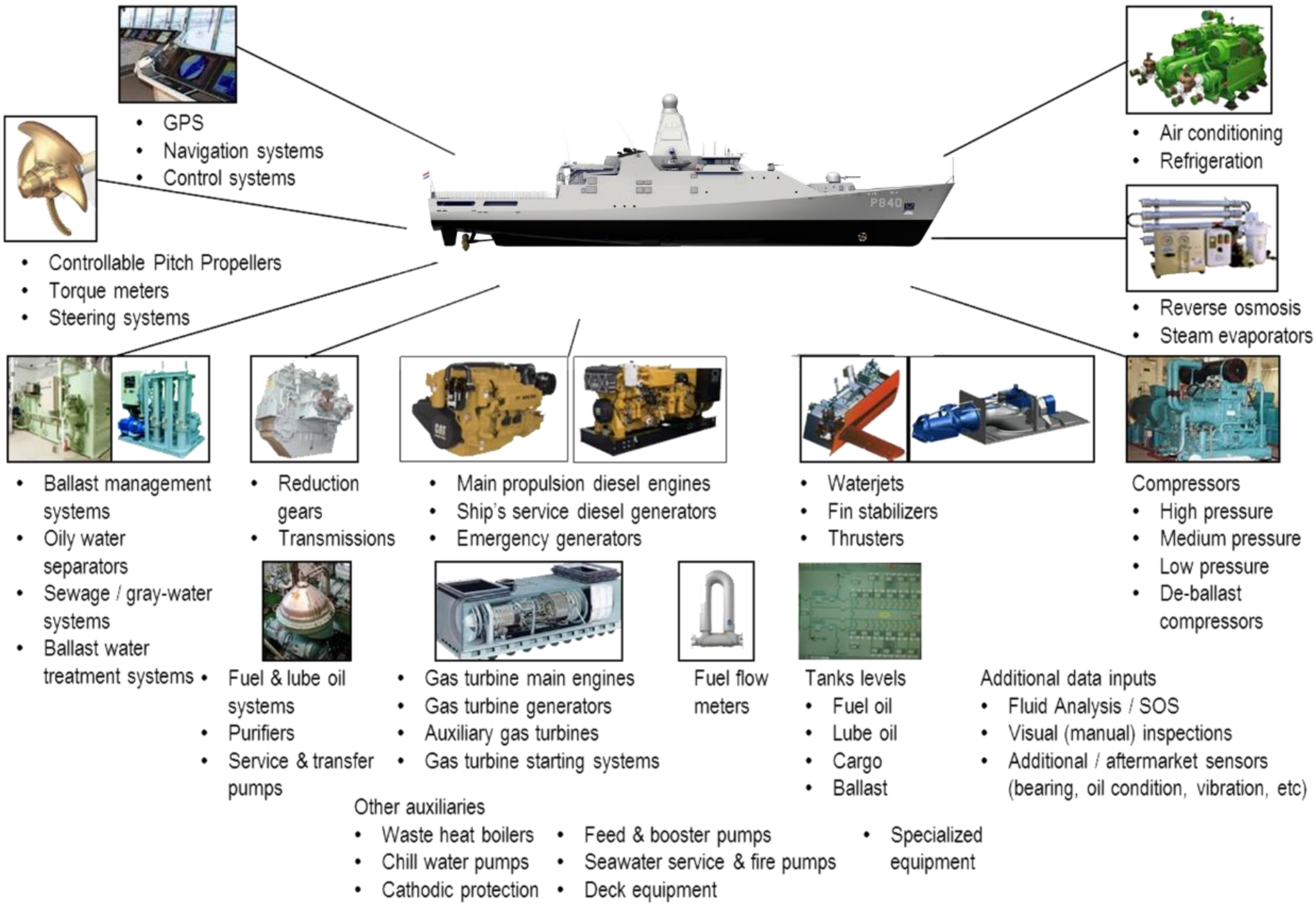
- Accuracy in the prediction can be relatively low, moreover in off design conditions.
- Availability of technical details are often not easy to get access to.

The Black Box Approach

- 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

Ship Energy Systems Modelling

The Black Box Approach



The Black Box Approach

A set of data $D_n = \{(\boldsymbol{x}_1, y_1), \cdots (\boldsymbol{x}_n, y_n)\}$, with $\boldsymbol{x}_i \in \mathcal{X} \subseteq \mathbb{R}^d$ and $y_i \in \mathcal{Y} \subseteq \mathbb{R}$ are available from the **automation system**.

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

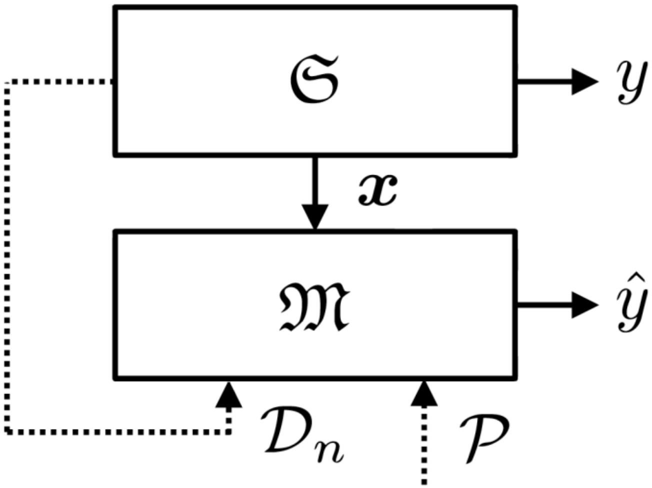
Dataset

Sample	Input Features						Output Feature
	Feature 1	Feature 2	…	Feature j	…	Feature d	
1	x_{11}	x_{12}	…	x_{1j}	…	x_{1d}	y_1
2	x_{21}	x_{22}	…	x_{2j}	…	x_{2d}	y_2
…	…	…	…	…	…	…	…
i	x_{i1}	x_{i2}	…	x_{ij}	…	x_{id}	y_i
…	…	…	…	…	…	…	…
n	x_{n1}	x_{n2}	…	x_{nj}	…	x_{nm}	y_n

Table 3: Variable of Table 2 exploited to built the $\mathfrak{M}$.

id	Name	Type
1	Latitude	Input
2	Longitude	Input
3	Volume	Input
4	State	Input
5	Auxiliary consumed	Input
6	Auxiliary electrical power output	Input
8	Shaft rpm	Input
9	Ship draft (fore)	Input
10	Ship draft (aft)	Input
11	Relative wind speed	Input
12	Relative wind direction	Input
13	GPS heading	Input
14	GPS speed	Input
15	Log speed	Input
16	Shaft generator power	Input
17	Sea depth	Input
18	Draft Port	Input
19	Draft Starboard	Input
20	Sea Water Temperature	Input
21	CPP Setpoint	Input
22	CPP Feedback	Input
23	Fuel Density	Input
24	Fuel Temperature	Input
25	Ambient Pressure	Input
26	Humidity	Input
27	Dew Point Temperature	Input
29	Rudder Angle	Input
30	Acceleration X Direction	Input
32	Acceleration Y Direction	Input
32	Acceleration Z Direction	Input
33	GyroX	Input
34	GyroY	Input
35	GyroZ	Input
36	Roll	Input
37	Pitch	Input
38	Yaw	Input
39	True direction	Input
40	True speed	Input
41	Beaufort	Input

The Black Box Approach



When **inferring** a model starting from a real system, the goal is to provide an **approximation** $\mathfrak{M}: \boldsymbol{x} \rightarrow y$ of the unknown true model $\mathfrak{S}: \boldsymbol{x} \rightarrow y$

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

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

Performance indicators:

$$\text{MAE} = \frac{1}{m}\sum_{i=1}^{m} |y_i - \hat{y}_i|$$

mean absolute error (MAE)

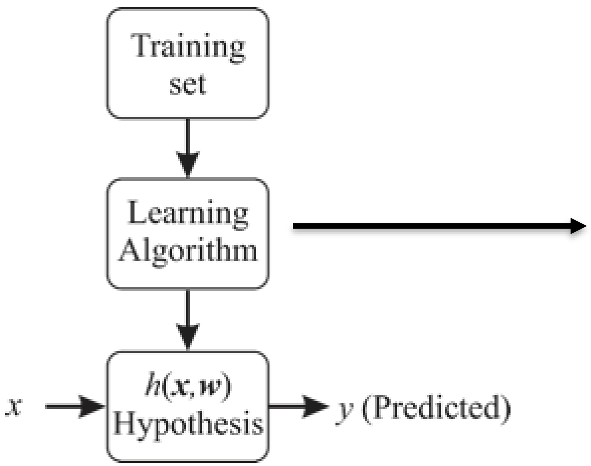
$$\text{MSE} = \frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

mean square error (MSE)

$$\text{REP} = 100\sqrt{\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m} {y_i}^2}}$$

relative error percentage (REP)

The Black Box Approach



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;

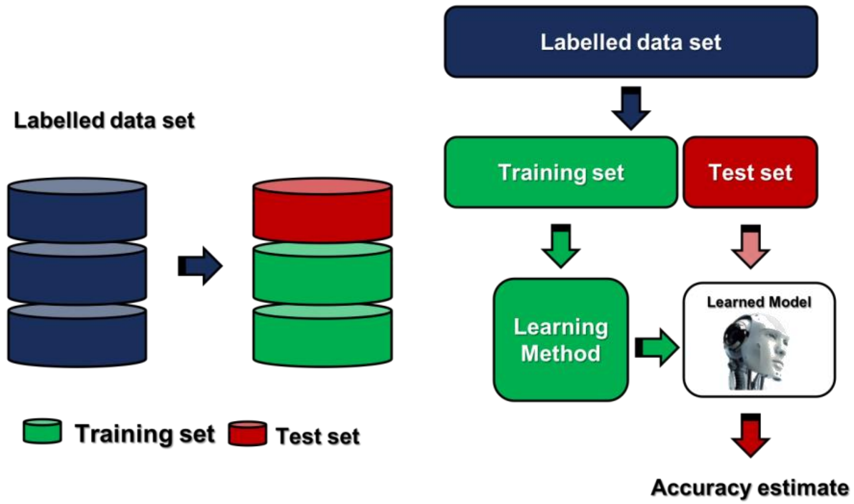
(ii) The trained model is used for prediction and control of the real system (feed-forward phase).

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

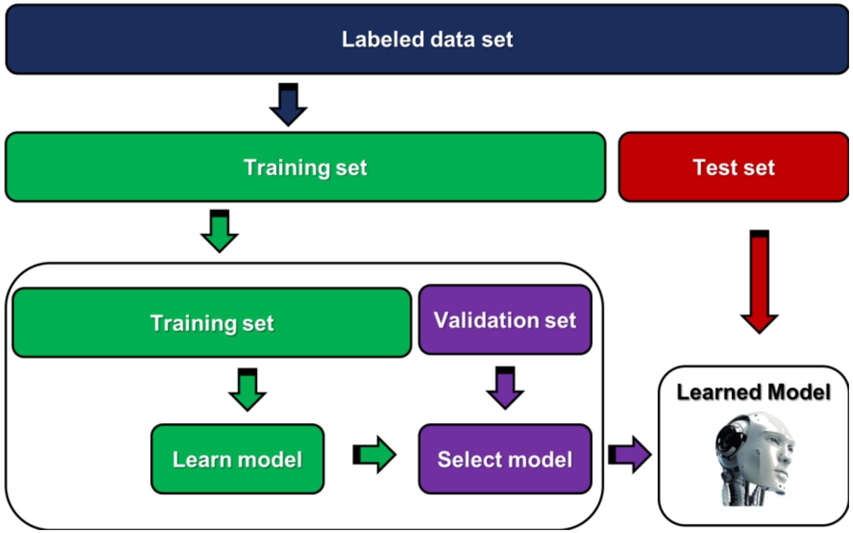
During the training phase, the quality of the regressor $h(x)$ is measured according to a loss function which calculates the discrepancy between the true and the estimated output (y and $\hat{y}$).

The Black Box Approach: Cross Validation

2-way data split



3-way data split



The Black Box Approach: Cross Validation –

Labeled data set

Training set

Test set

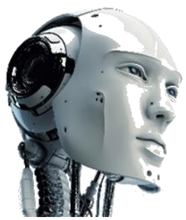
Training set

Validation set

Learn model

Select model

Learned Model



Ship Energy Systems Modelling

The Black Box Approach: Model Selection

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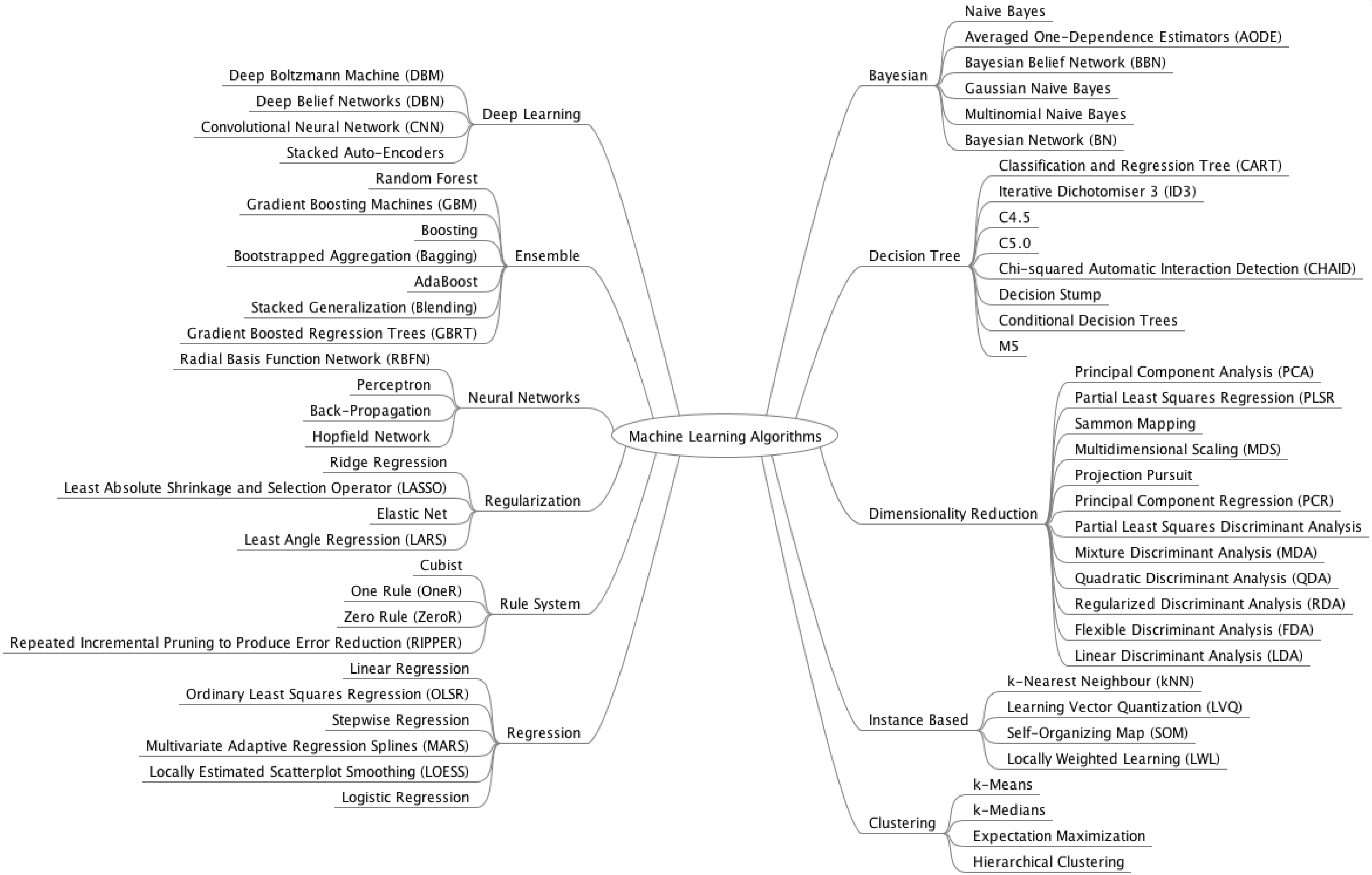


The Black Box Approach: Model Selection

Hyper Parameters

Supported Vector Machines:

$$f(\boldsymbol{x}) = \boldsymbol{w} \cdot \phi(\boldsymbol{x}) + b$$

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

$$s.t. \quad y_i(\boldsymbol{w} \cdot \phi(\boldsymbol{x}_i) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0, \quad i \in \{1, \cdots, n\}$$

$$\min_{\alpha} \quad \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\,\alpha_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j) - \sum_{i=1}^{n}\alpha_i$$

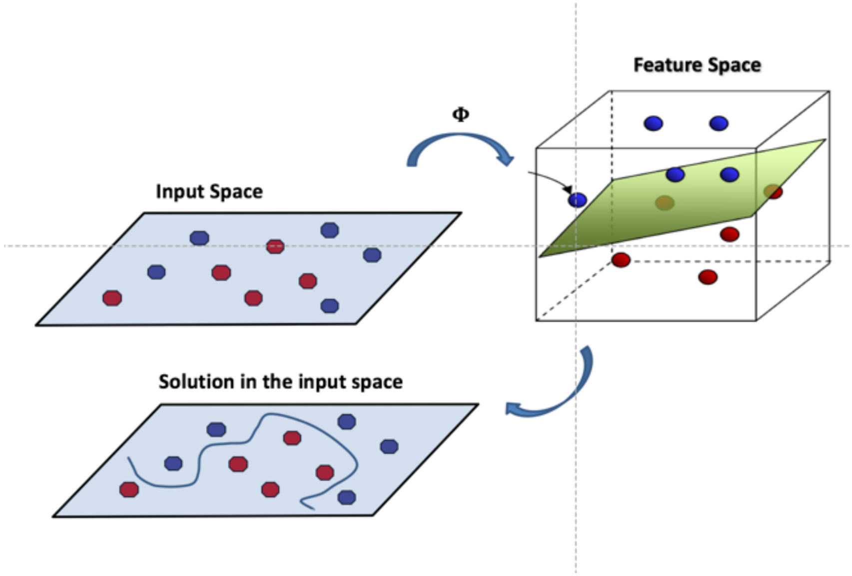
$$s.t. \quad 0 \leq \alpha_i \leq \boldsymbol{C}$$

$$\sum_{i=1}^{n} y_i\,\alpha_i = 0$$

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} y_i \alpha_i K(\boldsymbol{x}_i, \boldsymbol{x}_j) + b$$

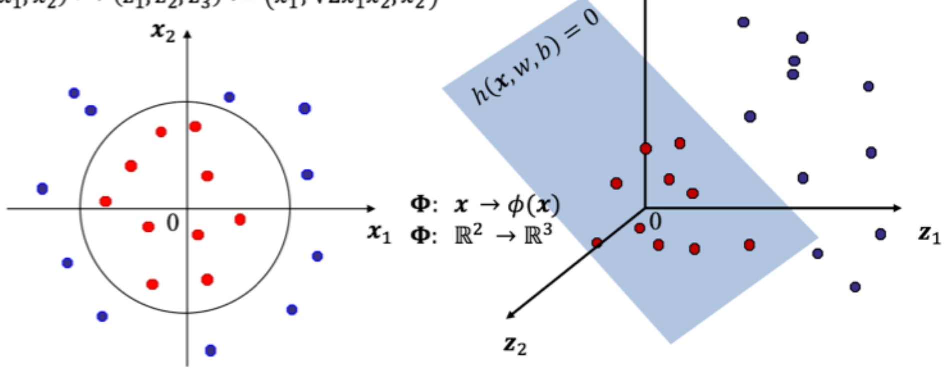
$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = e^{-\gamma\|x_i - x_j\|_2^2}$$

In this case the hyper-parameters are two: $\boldsymbol{C}$ and the kernal hyperparameter $\boldsymbol{\gamma}$.



the original input space can be mapped to some higher-dimensional feature space where the training set is separable

$$(x_1, x_2) \mapsto (z_1, z_2, z_3) := (x_1^2, \sqrt{2}x_1x_2, x_2^2)$$



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:

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

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

λ : 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 $\boldsymbol{\lambda}$ and the kernal hyperparameter $\boldsymbol{\gamma}$.

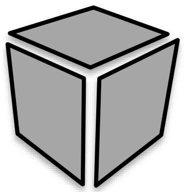
Artificial Neural Network (ANN)

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 $\boldsymbol{x}$, and allows the creation of a new dataset.

$$D_n^{WBM} D_n = \left\{ \left(\begin{bmatrix} \boldsymbol{x}_1 \\ h_{WBM}(\boldsymbol{x}_1) \end{bmatrix}, y_1 \right), \cdots, \left(\begin{bmatrix} \boldsymbol{x}_n \\ h_{WBM}(\boldsymbol{x}_n) \end{bmatrix}, y_n \right) \right\}$$

Dataset								
Sample	Input Features							Output Feature
	Feature 1	Feature 2	…	Feature j	…	Feature d	Feature $d+1$	
1	x_{11}	x_{12}	…	x_{1j}	…	$x_{1\mathrm{d}}$	$h_{WBM}(x_{1d+1})$	y_1
i	$x_{\mathrm{i}1}$	$x_{\mathrm{i}2}$	…	$x_{\mathrm{i}j}$	…	x_{id}	$h_{WBM}(x_{id+1})$	y_{i}
n	x_{n1}	x_{n2}	…	x_{nj}	…	x_{nm}	$h_{WBM}(x_{nd+1})$	y_n

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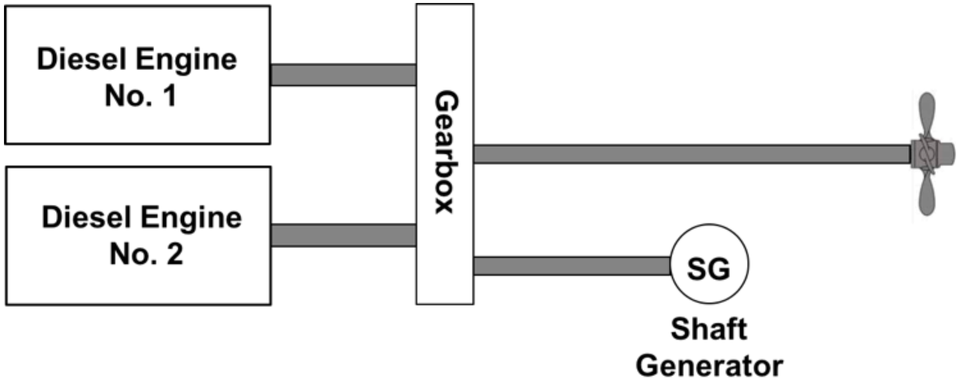
Case Study

Tosca



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]

Case Study

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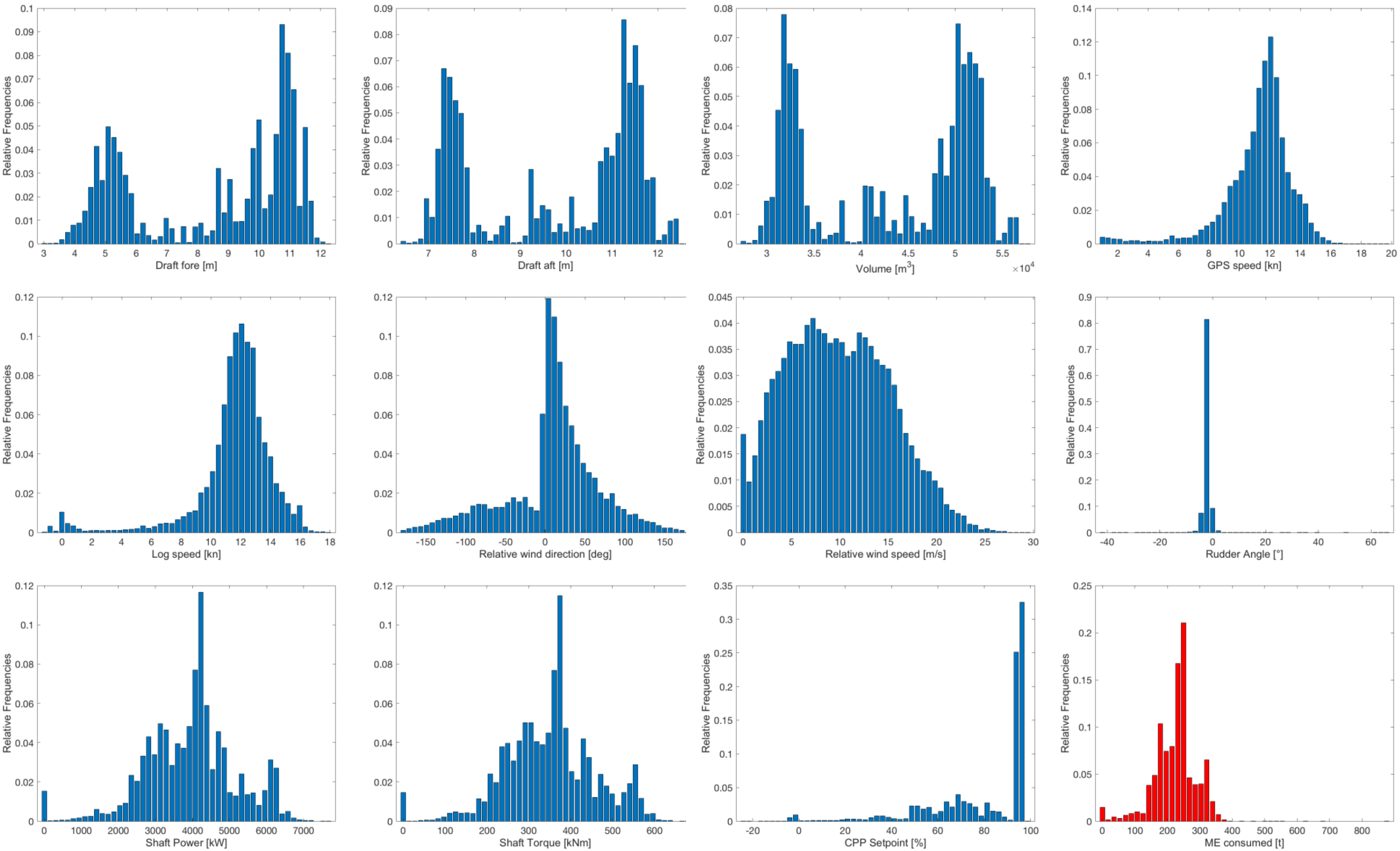

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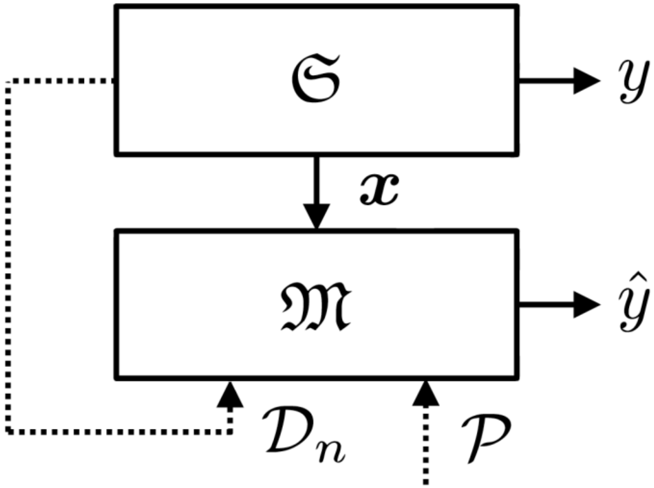
Data available from 20/03/2012 to 03/10/2014

Feature	Variable name	Unit	Feature	Variable name	Unit
x_1	Time stamp	[t]	x_{18}	Sea depth	[m]
x_2	Latitude	[°]	x_{19}	Sea Water Temperature	[°C]
x_3	Longitude	[°]	x_{20}	CPP Set point	[°]
x_4	Auxiliary engines power output	[kg/h]	x_{21}	Fuel Density	[kg/m^3]
x_5	Shaft generator power	[kg/h]	x_{22}	Fuel Temperature	[°C]
x_6	Propeller shaft power	[kW]	x_{23}	Ambient Pressure	[bar]
x_7	Propeller speed	[rpm]	x_{24}	Relative Humidity	[%]
x_8	Ship draft (fore)	[m]	x_{25}	Dew Point Temperature	[°C]
x_9	Ship draft (aft)	[m]	x_{26}	Shaft Torque	[kN m]
x_{10}	Draft Port	[m]	x_{27}	Rudder Angle	[°]
x_{11}	Draft Starboard	[m]	x_{28}	Acceleration x Direction	[m/s^2]
x_{12}	Relative wind speed	[m/s]	x_{29}	Acceleration y Direction	[m/s^2]
x_{13}	Relative wind direction	[°]	x_{30}	Acceleration z Direction	[m/s^2]
x_{14}	GPS heading	[°]	x_{31}	Roll	[°]
x_{15}	Speed over ground	[knots]	x_{32}	Pitch	[°]
x_{16}	Speed through water	[knots]	x_{33}	Yaw	[°]
x_{17}	CPP Feedback	[°]	y	Main engines fuel consumption	[kg/h]

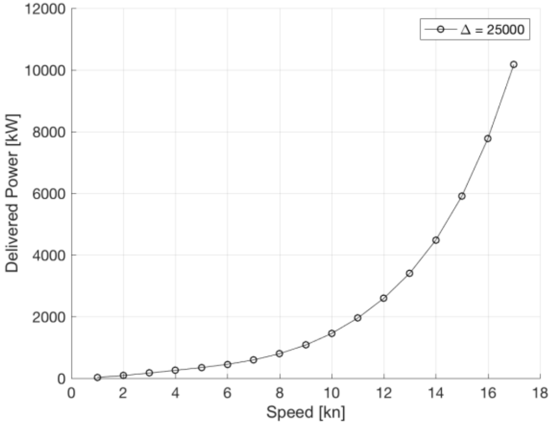


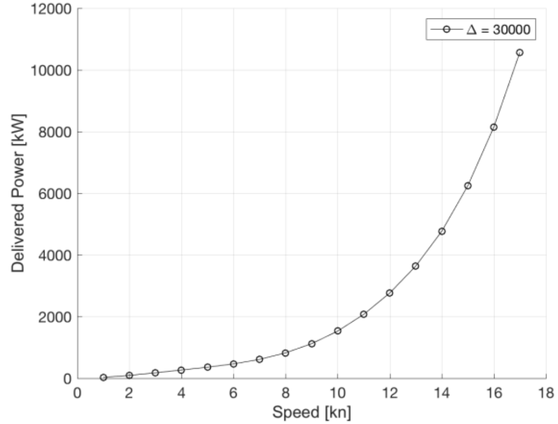
- **White Box Model**: the model is built based on a priori, mechanistic knowledge of $\mathfrak{S}$ (numerical description of the body hull, propulsion plant configuration, design information of the ship).

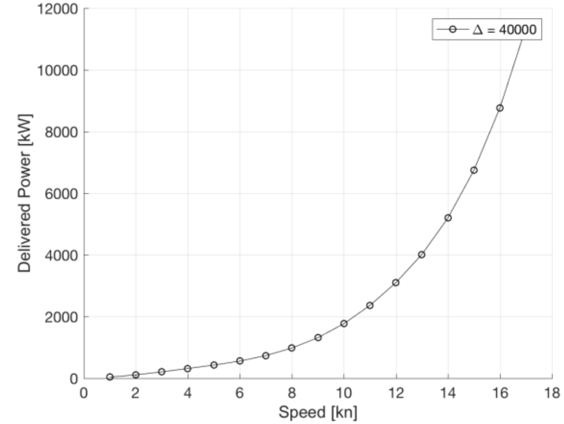
- **Black Box Model**: the model is built based on a series of historical observation of $\mathfrak{S}$ ($\mathfrak{D}_n$).

- **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 $\mathfrak{D}_n$ so to improve the performances of both the models.

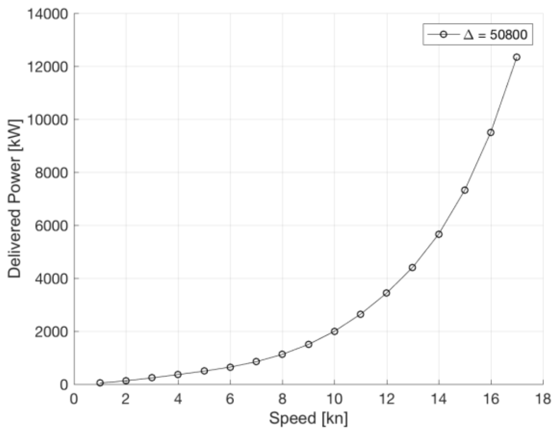
Resistance prediction model Calibration

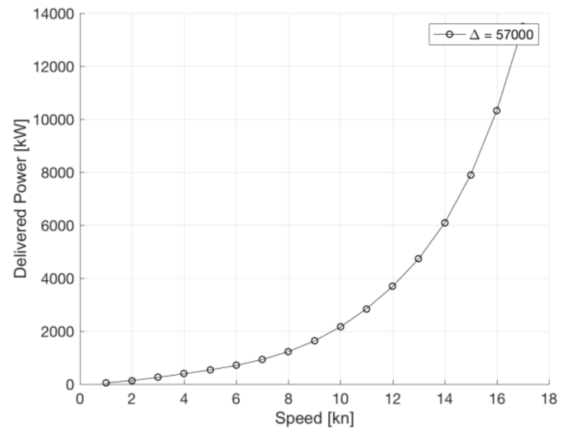






DELIVERED POWER FROM TRIALS @ different Displacements



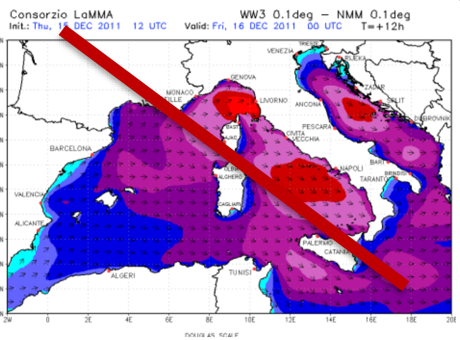


Resistance prediction PARAMETERS TUNING using real data from towing tank trials (Ideal conditions: no wind, waves, trim, rudder, …)

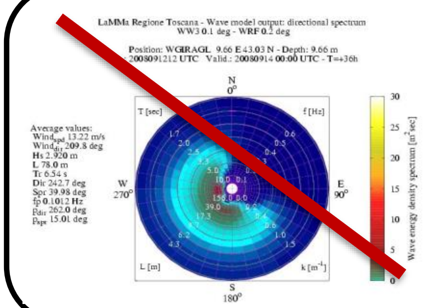
The White Box Approach

University of Strathclyde Glasgow

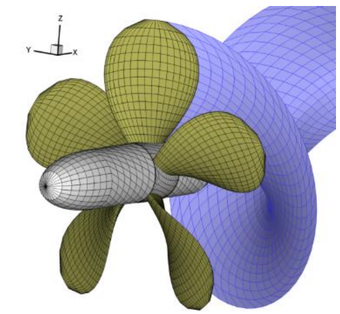
Wind Resistance



Waves Added Resistance



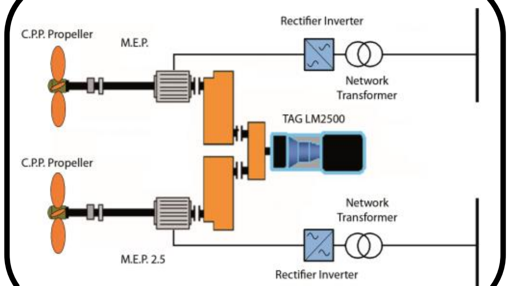
Propeller Performance



Fuel Consumption

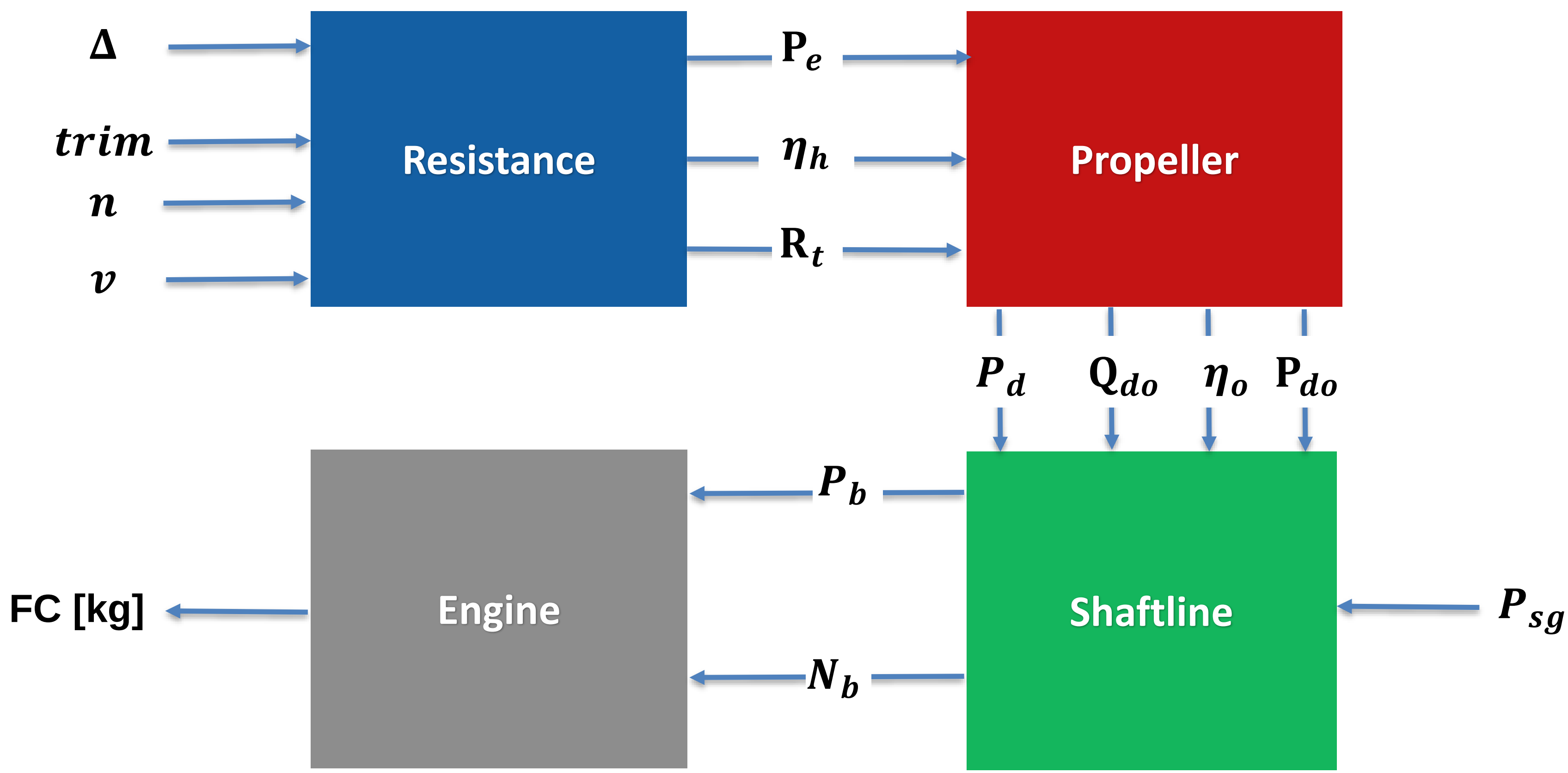
Calm Water Hull Resistance

Trade/route

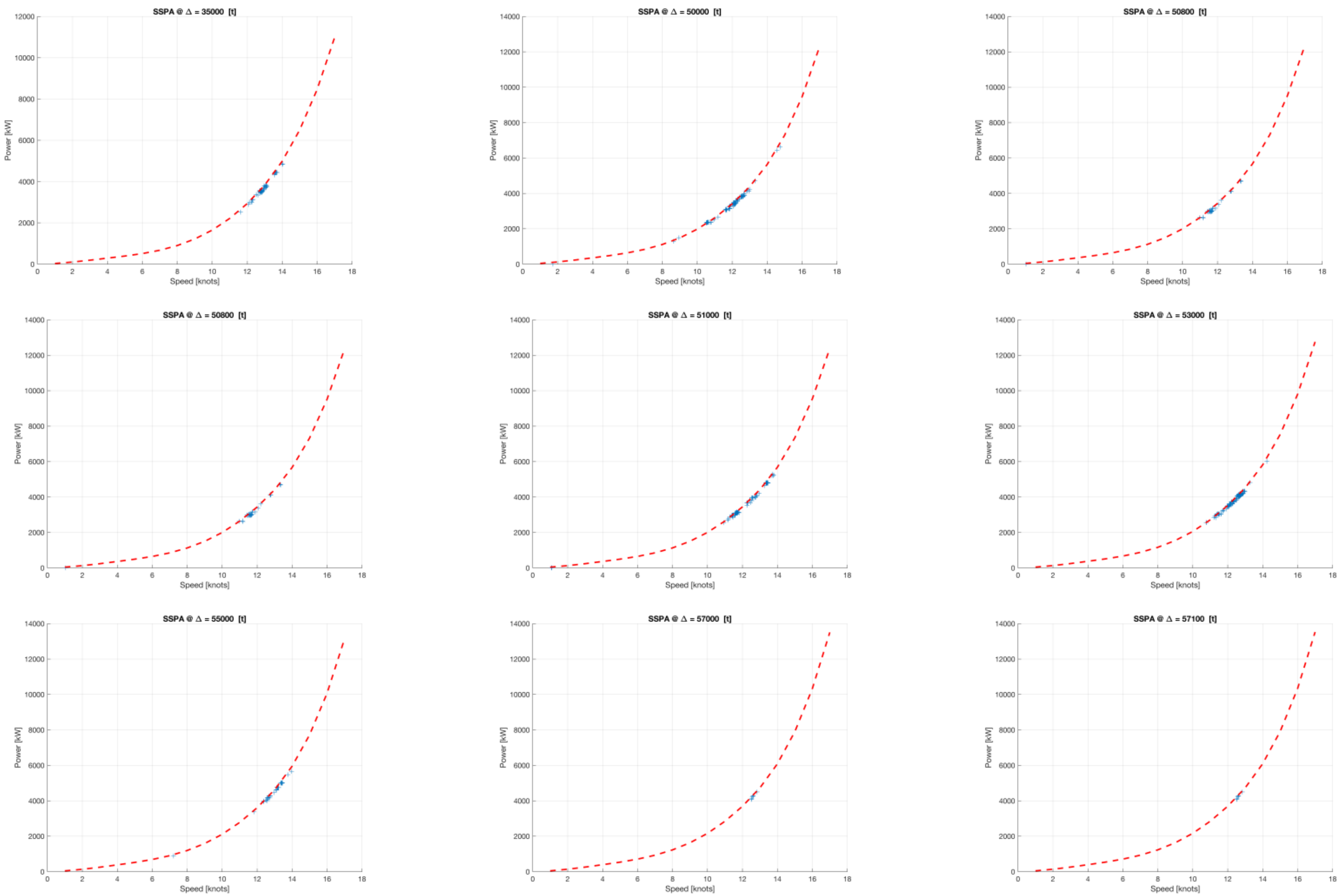


Propulsion Plant

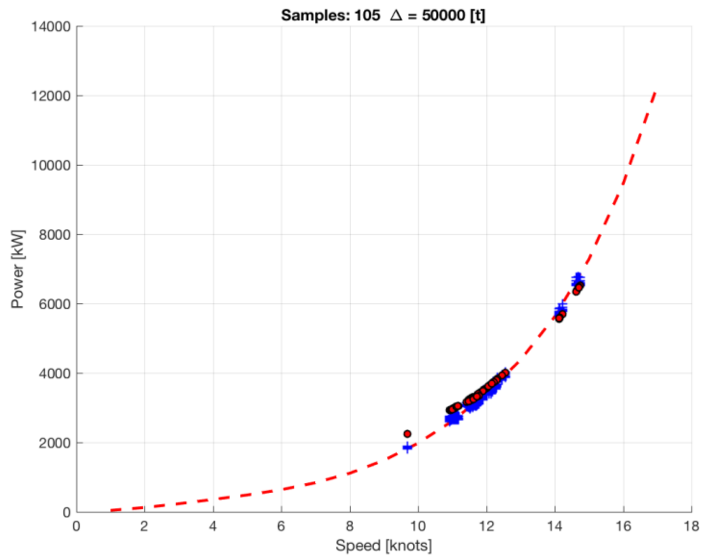
The White Box Approach

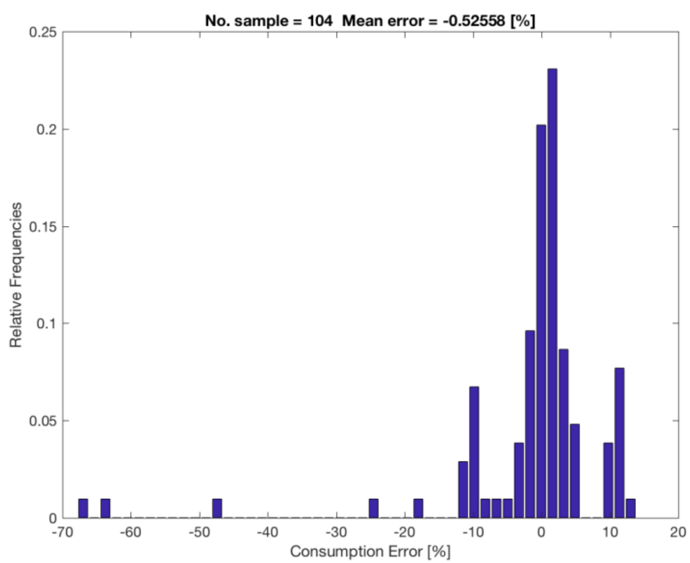


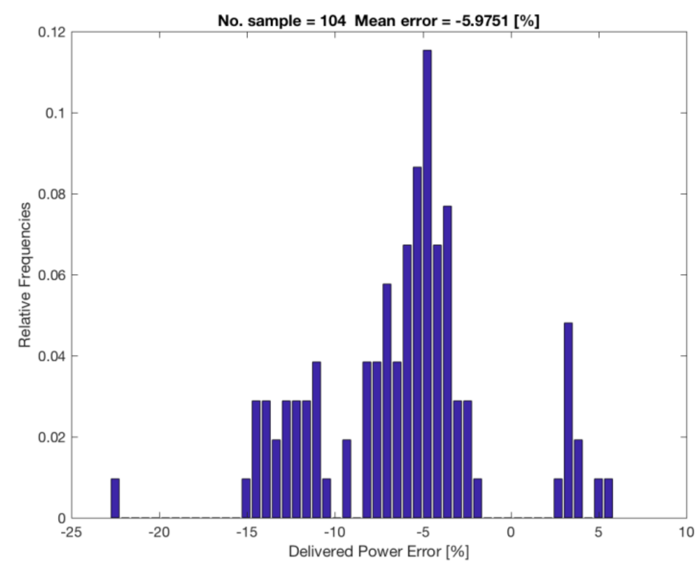
Validation on “Calm Water Scenario”



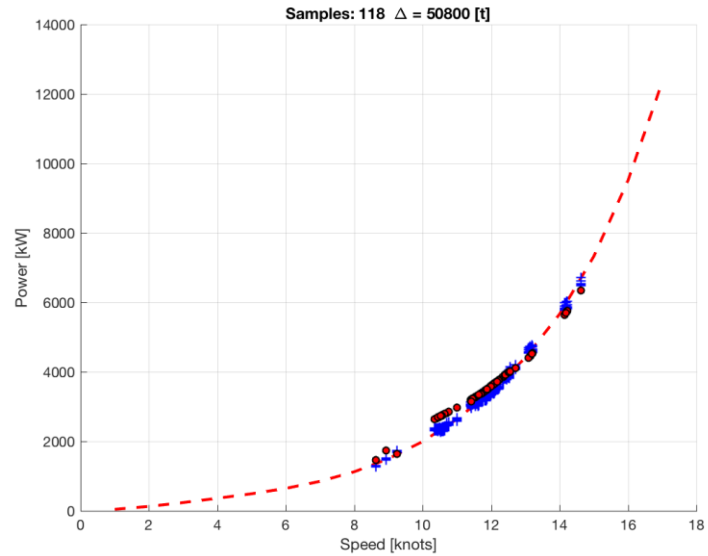
Validation on "Calm Water Scenario"

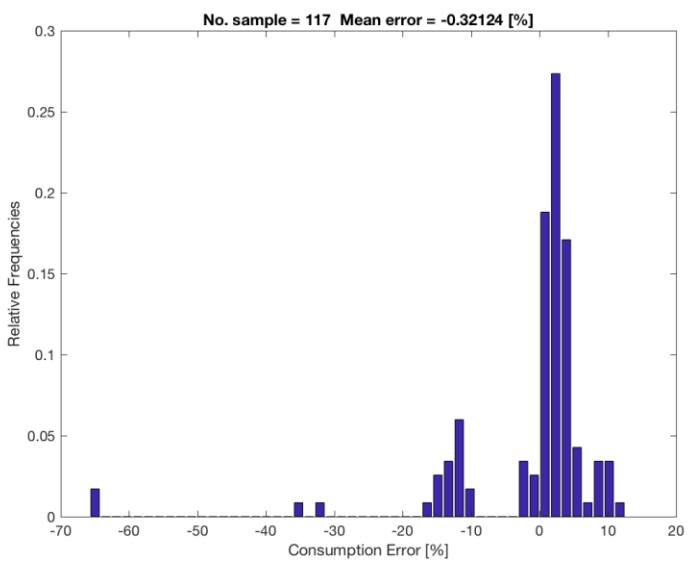


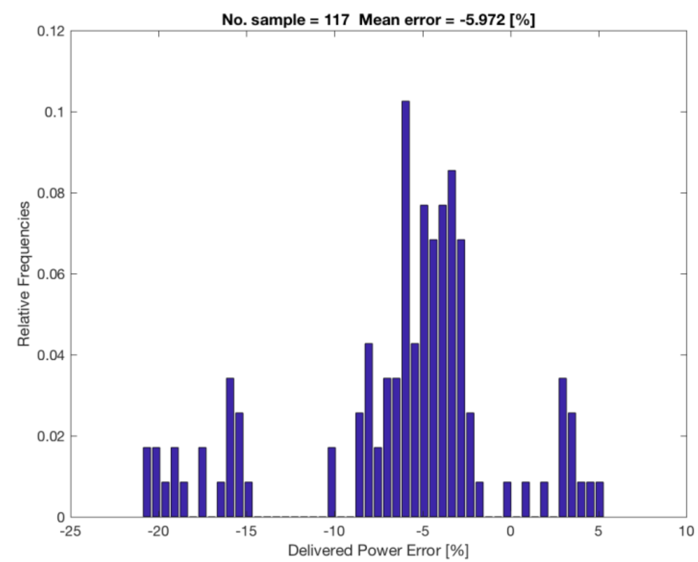




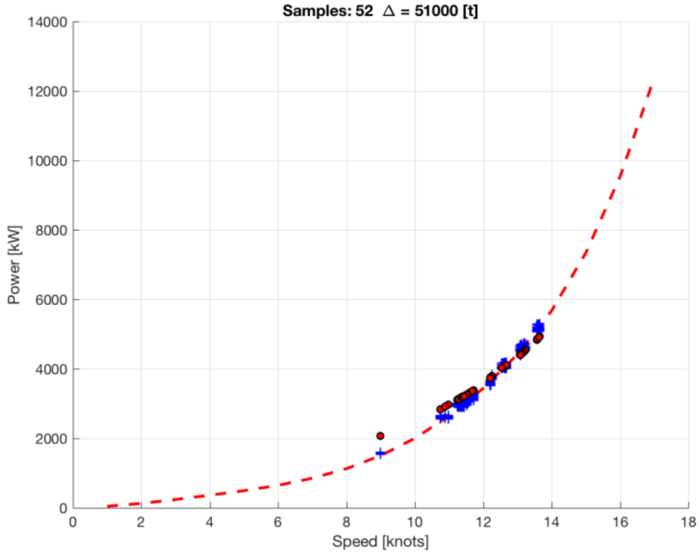
Validation on “Calm Water Scenario”

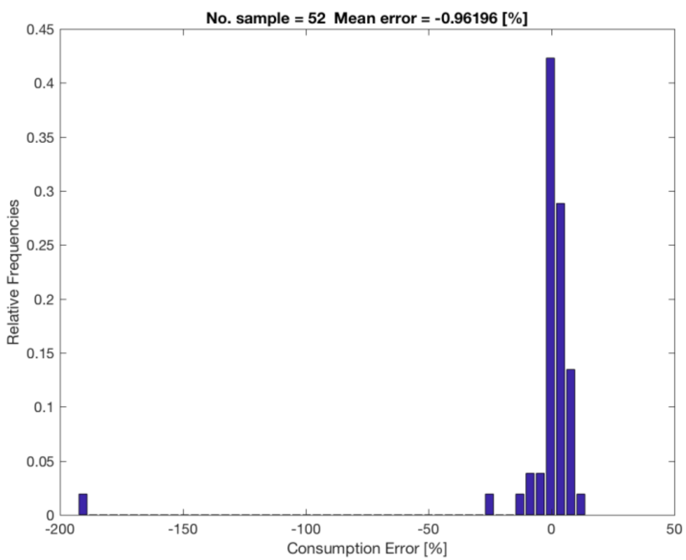


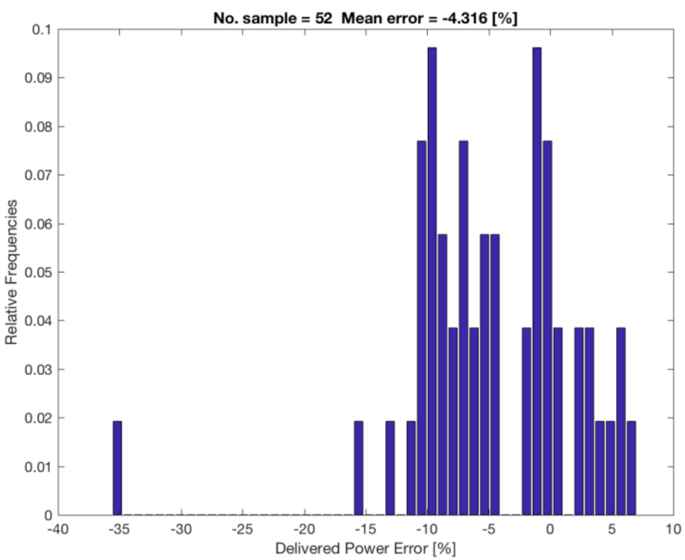




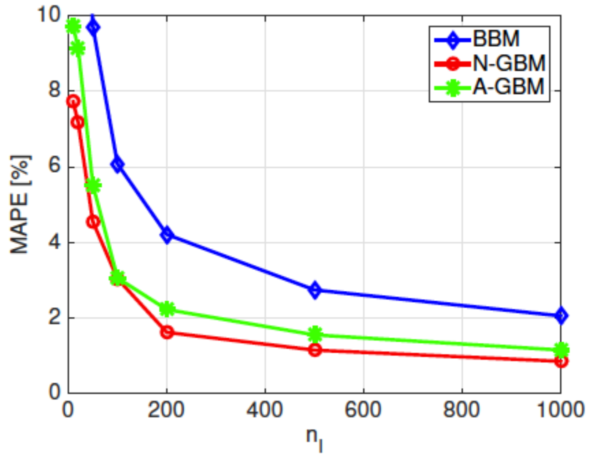
Validation on “Calm Water Scenario”



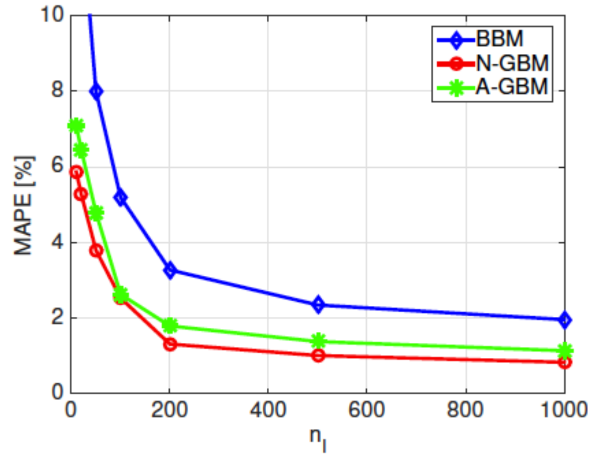




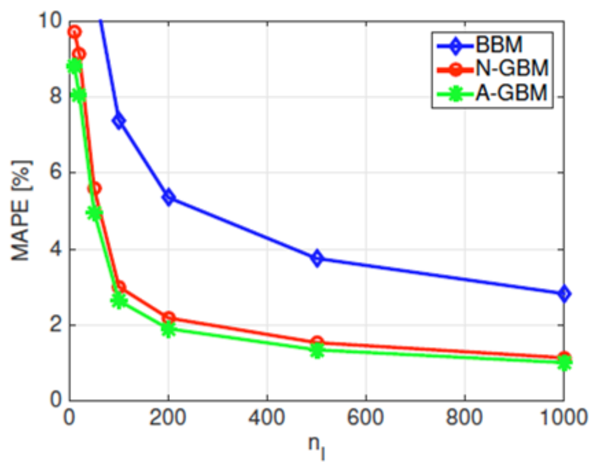
Black and Grey Models comparison



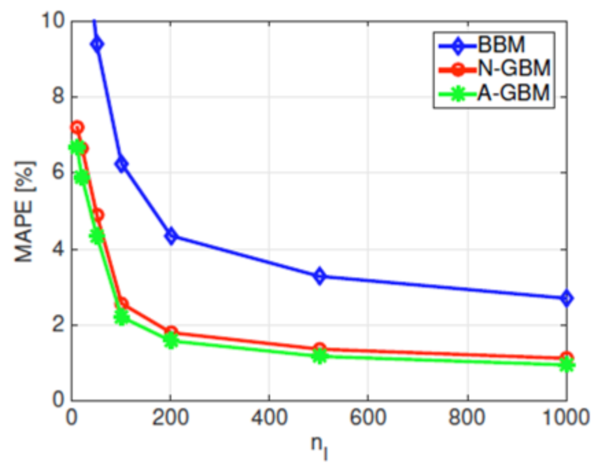
(h) RF Shaft Torque



(i) RF Fuel Consumption



(b) RLS Shaft Torque



(c) RLS Fuel Consumption

Conclusions

University of Strathclyde Glasgow

- 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

Acknowledgement

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