

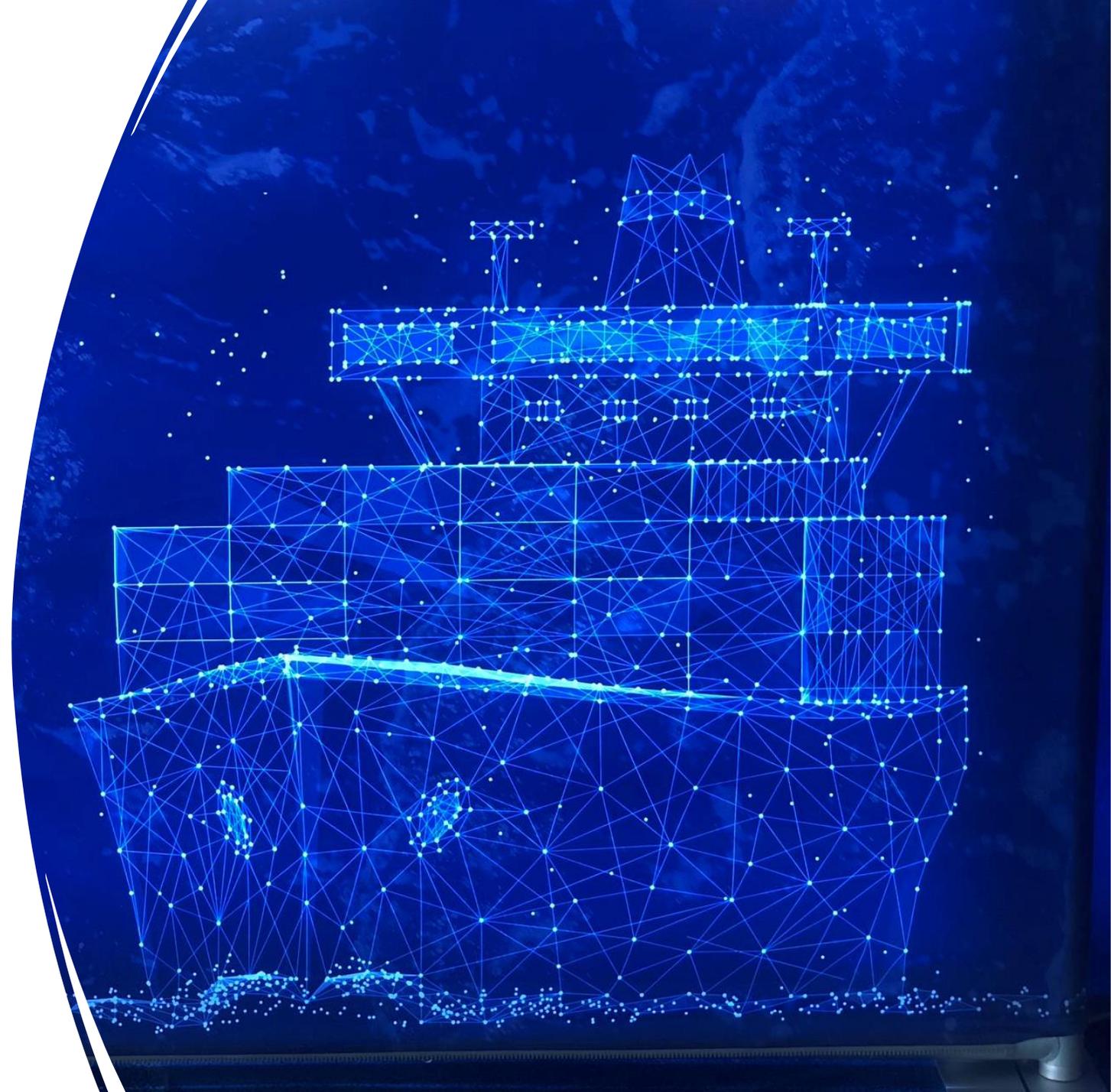
Artificial intelligence based digital twin models
to
monitor ship safety and efficiency

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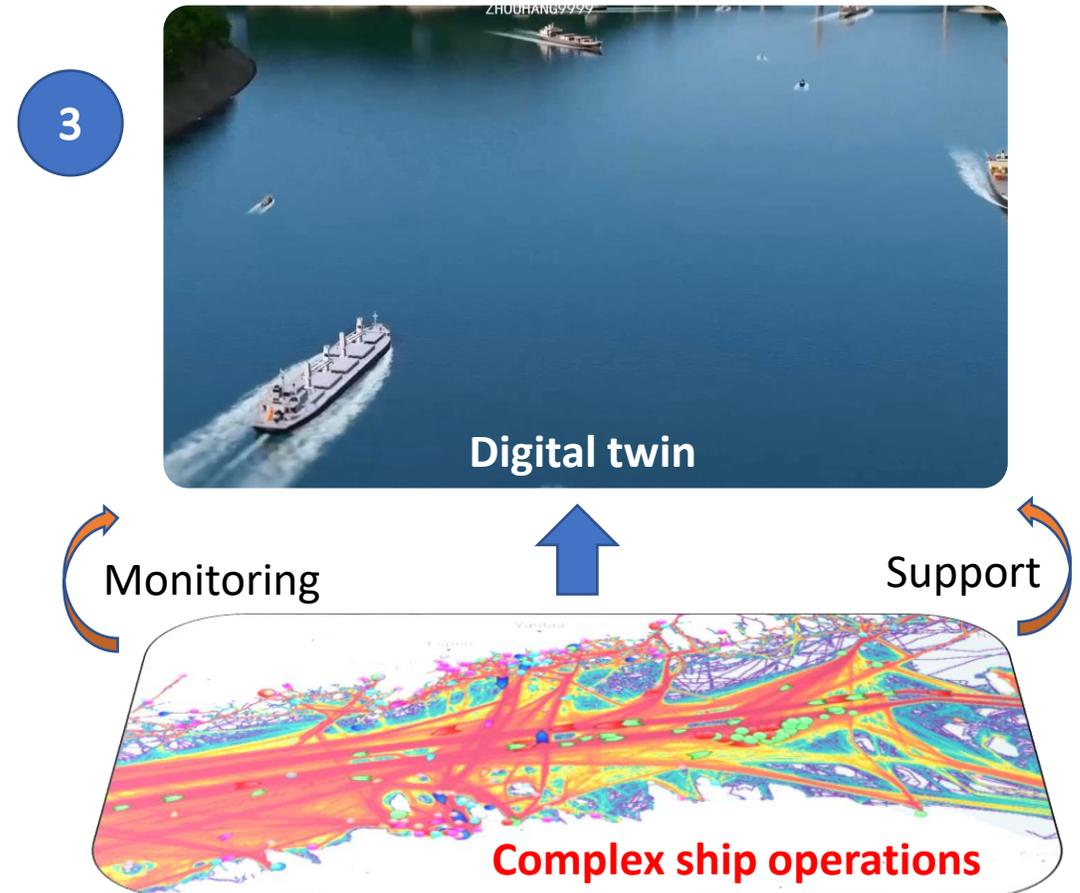
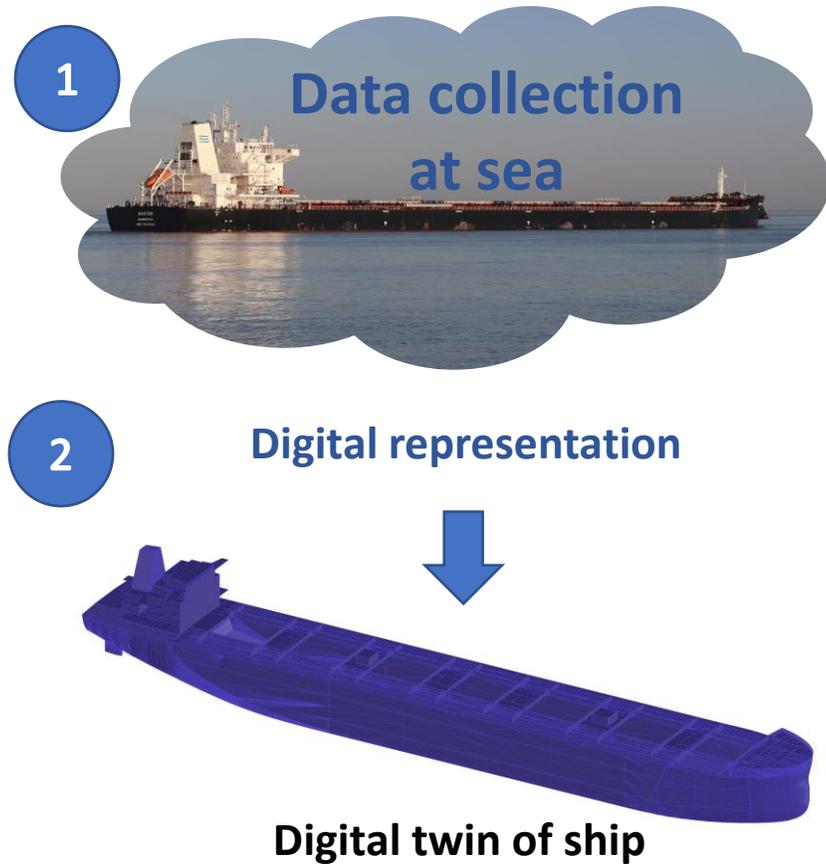
Contents

- **Background**
- **Research question**
- **Method**
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Ship digital twin

□ Data driven Digital twin



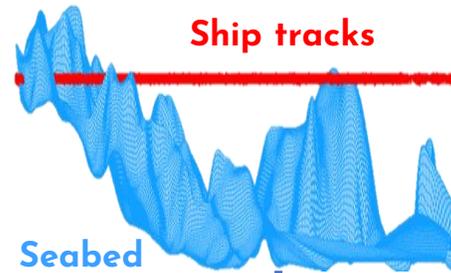
- allows for continuous **monitoring, analysis and optimization** .
- promote better decision support (safety and efficiency)

Research question

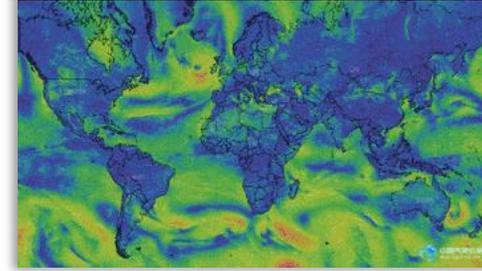
Complex traffic



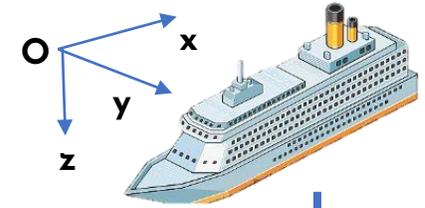
Complex waterways



Complex operational conditions



Uncertainty in ship dynamics



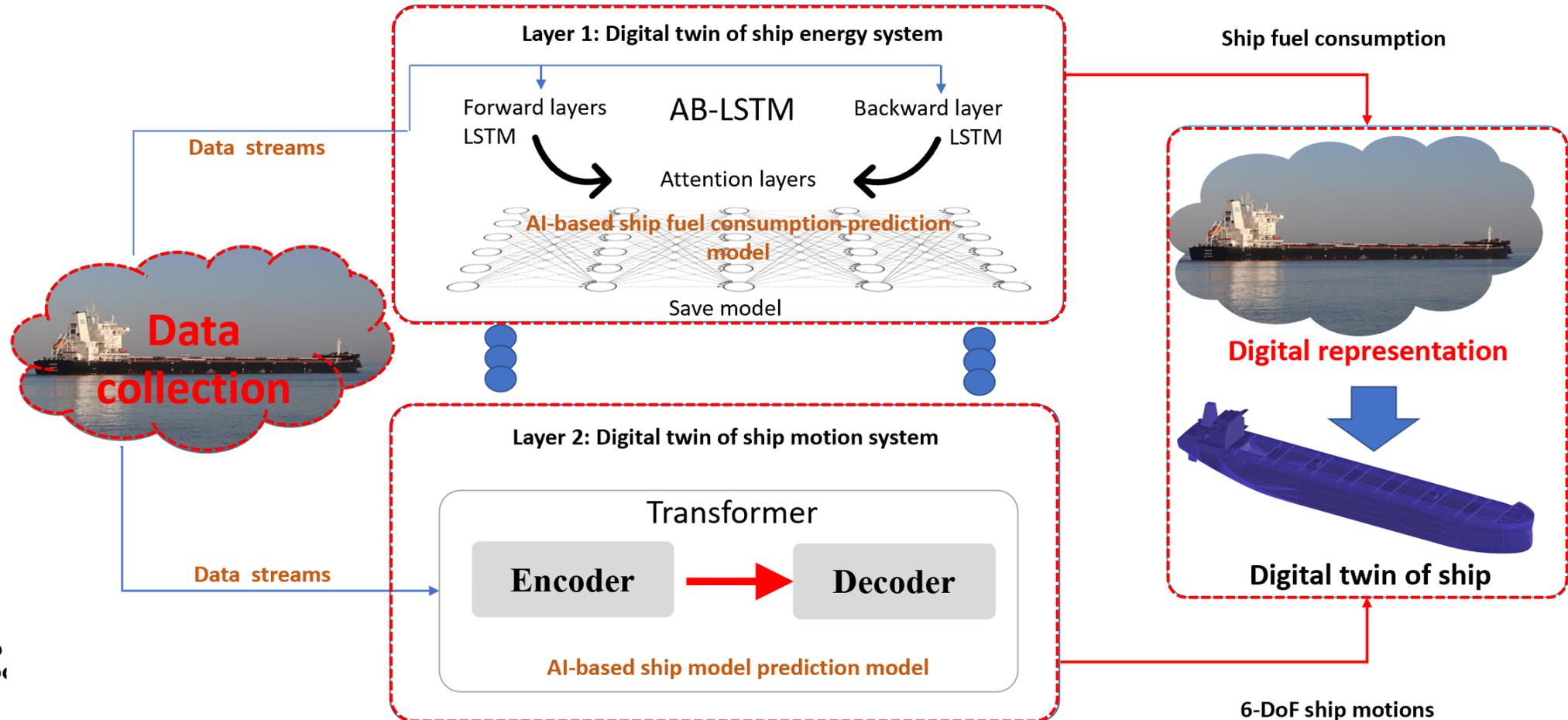
Digital twin development



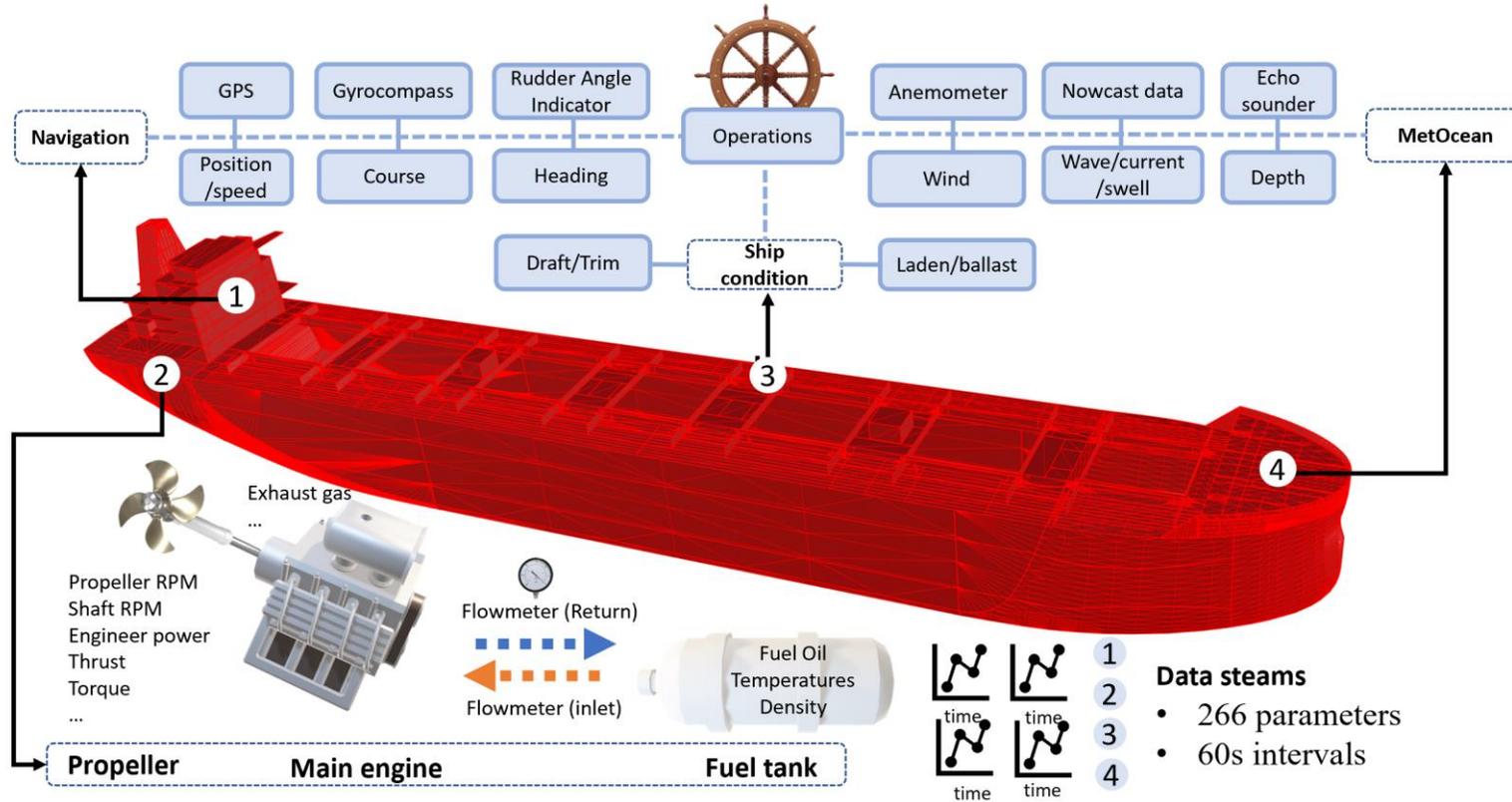
Can we use deep learning methods to capture ship systems and then optimize ship operations in real conditions?

Research focus – 2 main deep learning layers

- ❑ Big data collection at sea
- ❑ Idealisation of the operations of ship energy systems
- ❑ Idealisation of the operations of hull and propulsion systems



Method (1/3) – Big data collection

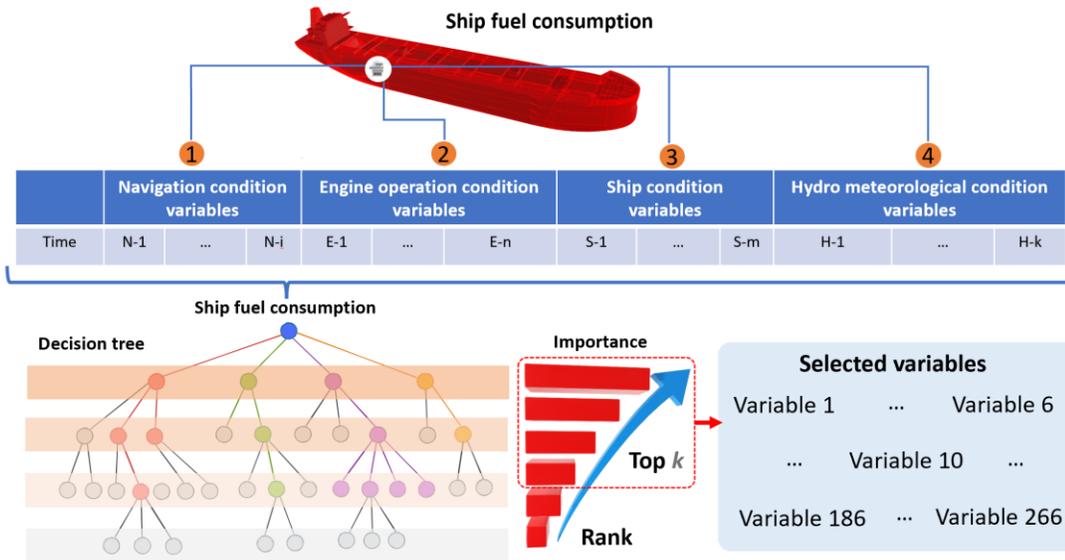


- Navigation data
- Ship condition data
- Ship engine data
- Hydrometeorological data



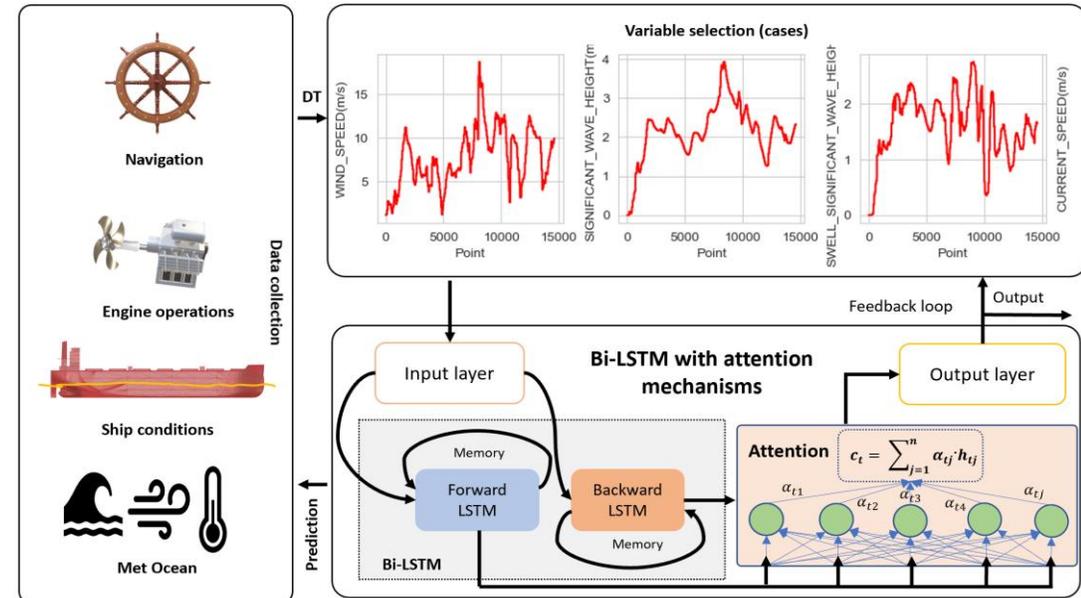
- ❖ Data from ship energy system
- ❖ Data from ship manoeuvring system

Methodology (2/3) – Ship energy systems

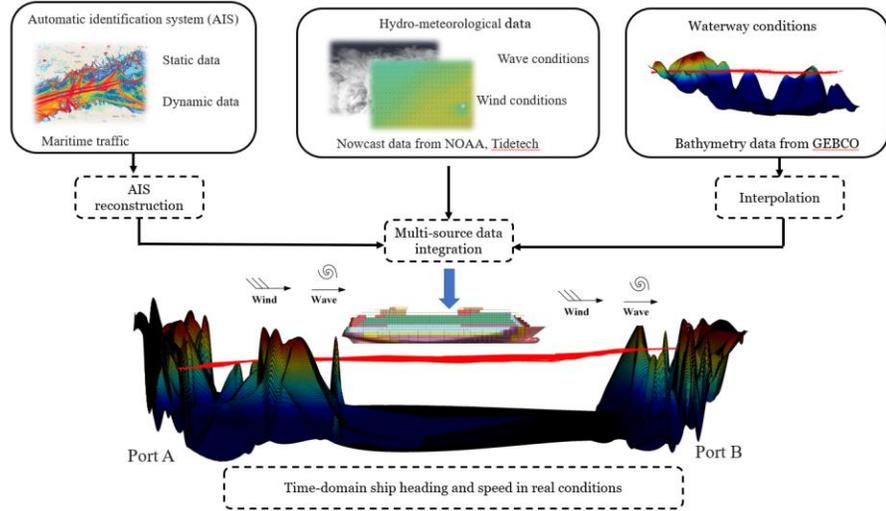


- ❖ Select key influencing factors on ship fuel consumption:
 - ✓ Navigation data (i.e., speed, heading, course, etc.)
 - ✓ Ship operation conditions (i.e., draft, trim, etc.)
 - ✓ Engine operations (i.e., fuel oil flow/ density, RPM, engine power)
 - ✓ Metocean data (i.e., air temperature, hydrometeorological data, etc.)

- ❖ Fuel consumption prediction layer
 - ✓ Attention mechanisms
 - ✓ Bidirectional Long Short-Term Memory (Bi-LSTM) networks



Methodology (3/3) – Hull motions & propulsion

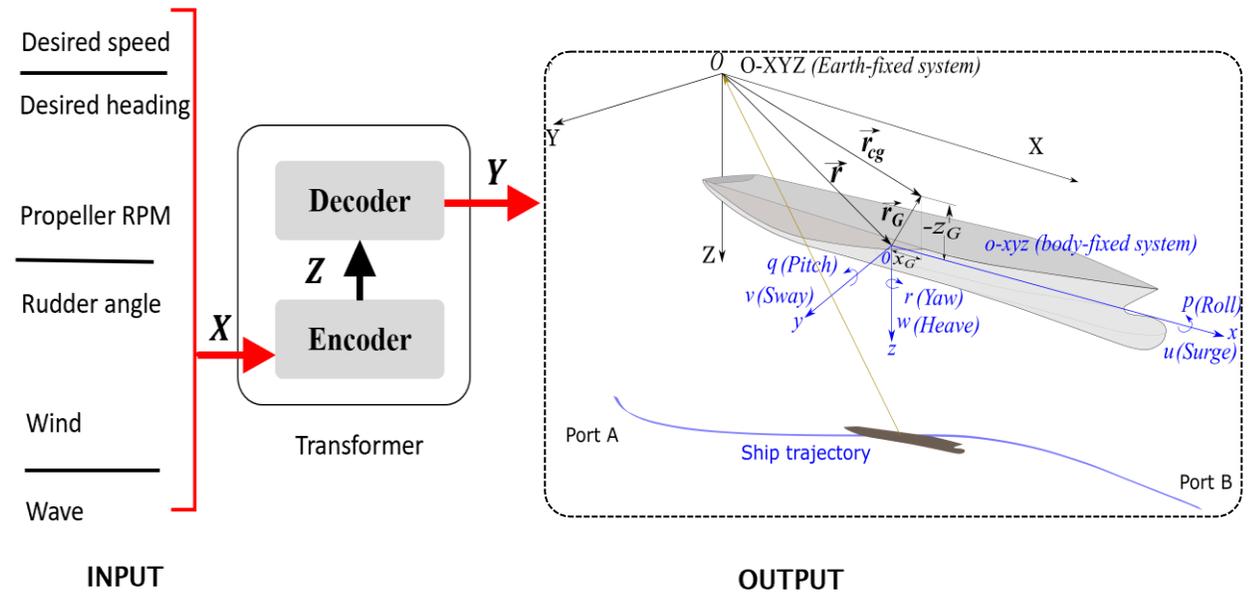


❖ To recover the real operational conditions

- *Ship maneuvering data (Rudder, RPM, speed, heading)*
- *6 DOF (Surge, Sway, Heave, Roll, Pitch, Yaw)*
- *Hydrometeorological conditions*
- *Bathymetry data*

❖ Ship motions prediction layer:

- *Transformer*
- *Generative Pre-trained Transformer*



Case studies

- ❑ Digital twin of ship energy system for the predictions of ship fuel consumption



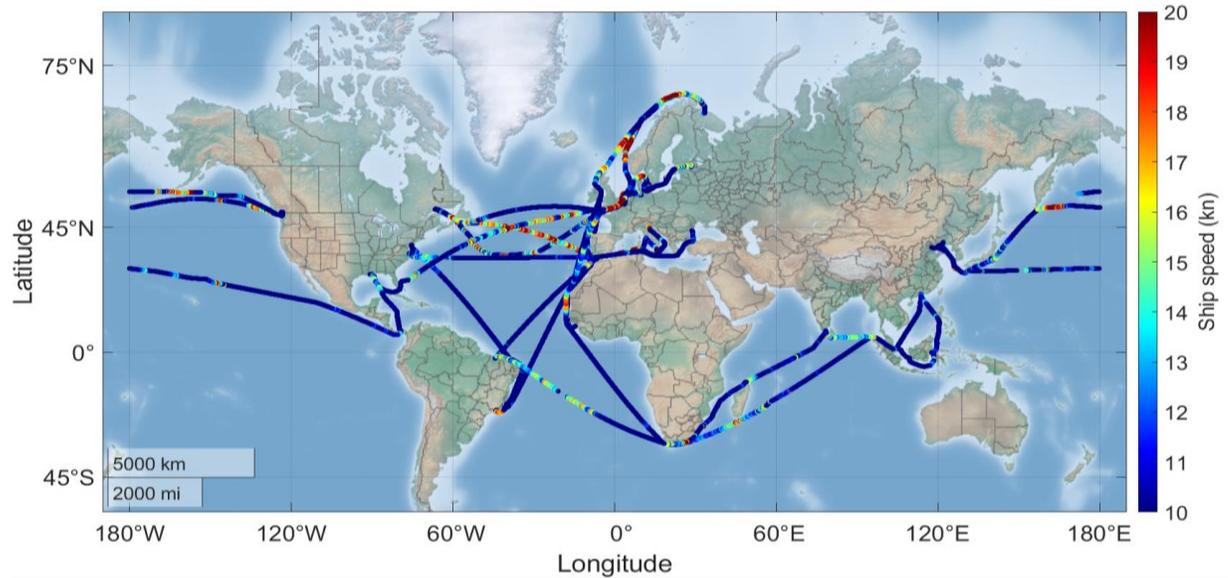
- ❑ IMO: 9843405
- ❑ Vessel Type : Bulk Carrier
- ❑ DWT: 81,600 t
- ❑ Length x Breadth : 229 x 32 m
- ❑ Year Built: 2020

- ❑ Digital twin of ship maneuvering system for 6 DOF prediction



- ❑ IMO: 9773064
- ❑ Vessel Type :Ro-Pax ship
- ❑ DWT: 49 134.0 t
- ❑ Length x Breadth : 212.0 x 30.6 m
- ❑ Year Built: 2017

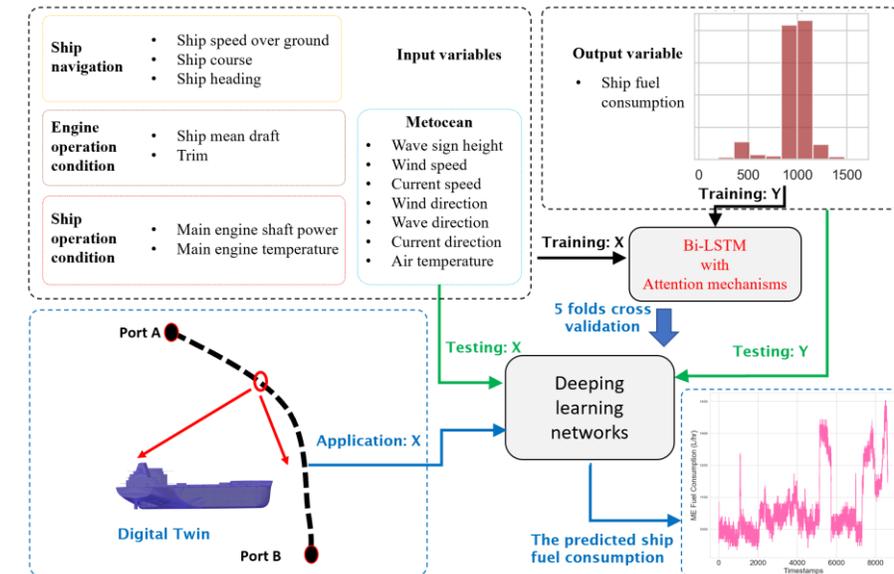
Results of layer 1 (data streams and model)



- MV KASTOR Bulker
- 01.02.21 - 10.02.23 (2 years)
- 53 different routes
- 60s intervals, more than 1M records

□ Model training and validation

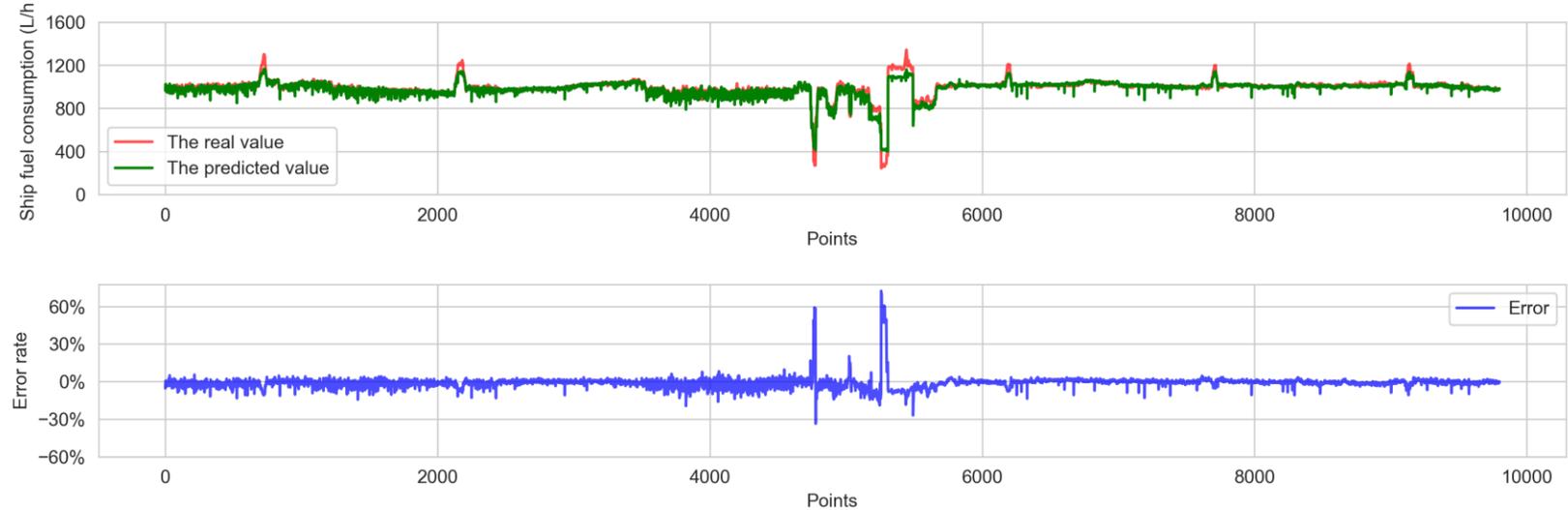
- Navigation, engine, ship operation and weather conditions set as inputs
- Ship fuel consumption set as outputs
- 80% of data used for training the model
- 20% of data used for validation



Results of layer 1 (model training / validation)

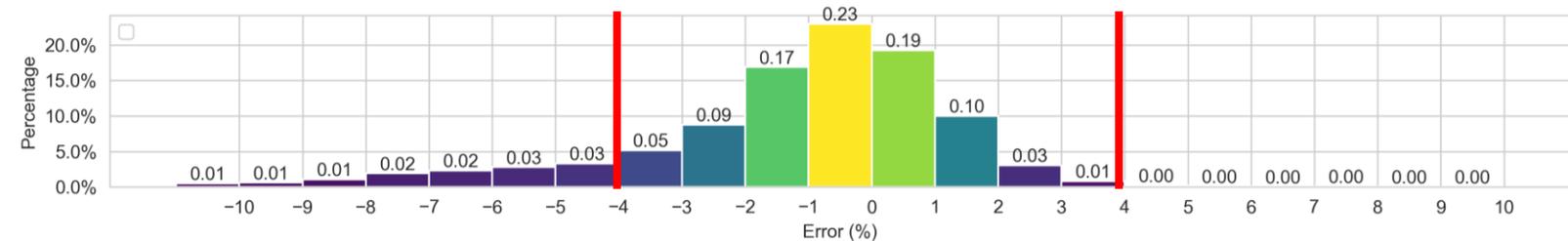
Comparison of real and predicted ship fuel consumption

- 5-fold cross validation
- The average validation loss using Mean Squared Error (MSE) is determined to be 0.0204.

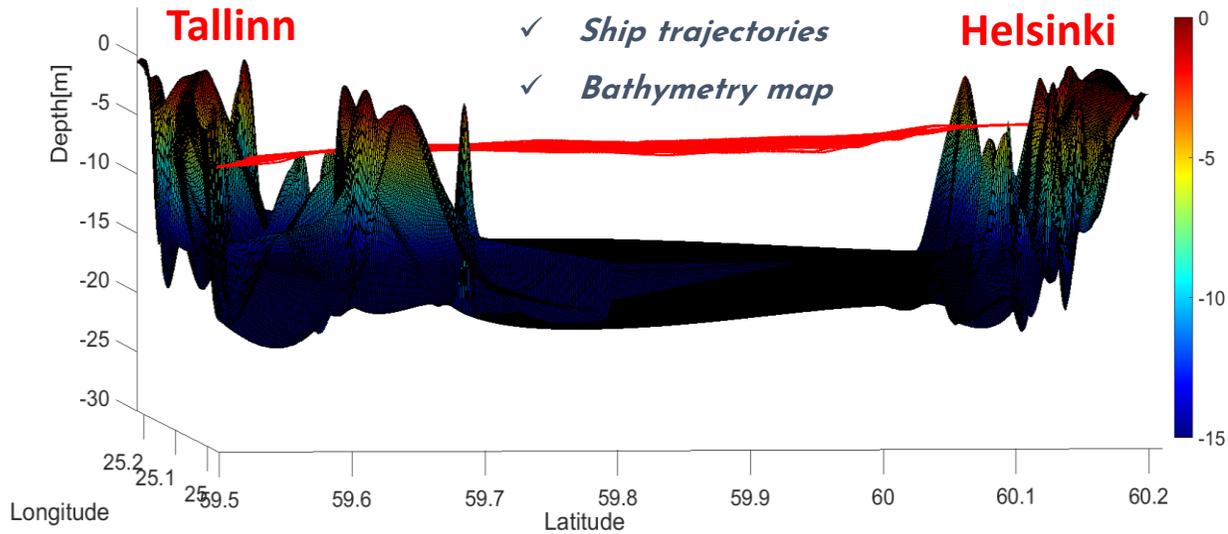


Prediction errors using the proposed model

- Over 90% of errors are below 4%, with an average error rate of 0.98%.



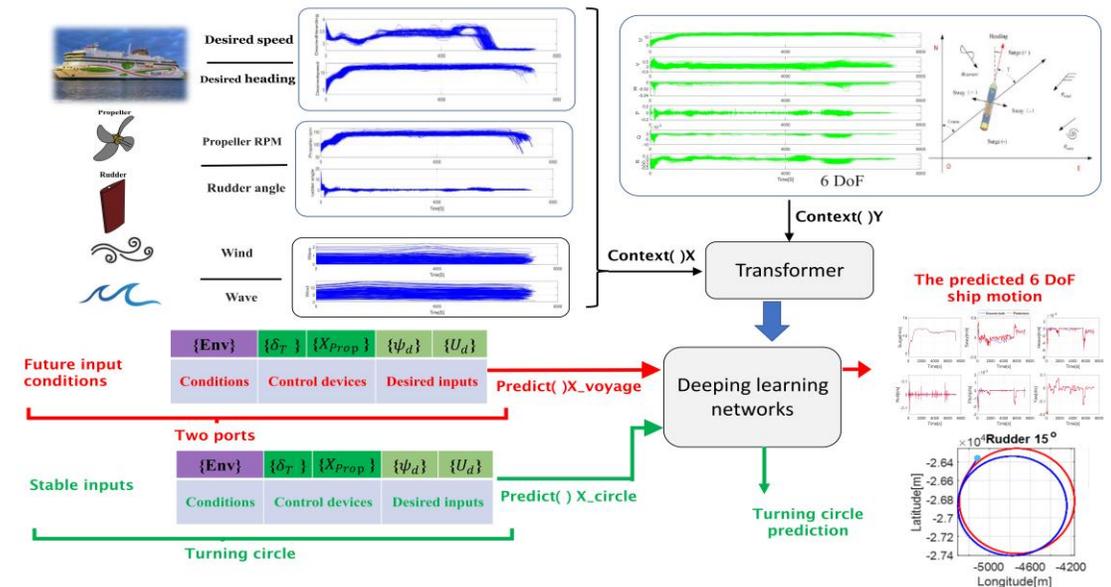
Results of layer 2 (data streams and model)



- Ro-Pax ship in Gulf of Finland
- 2018 - 2019 (ice free period)
- 500 different routes
- 60s intervals

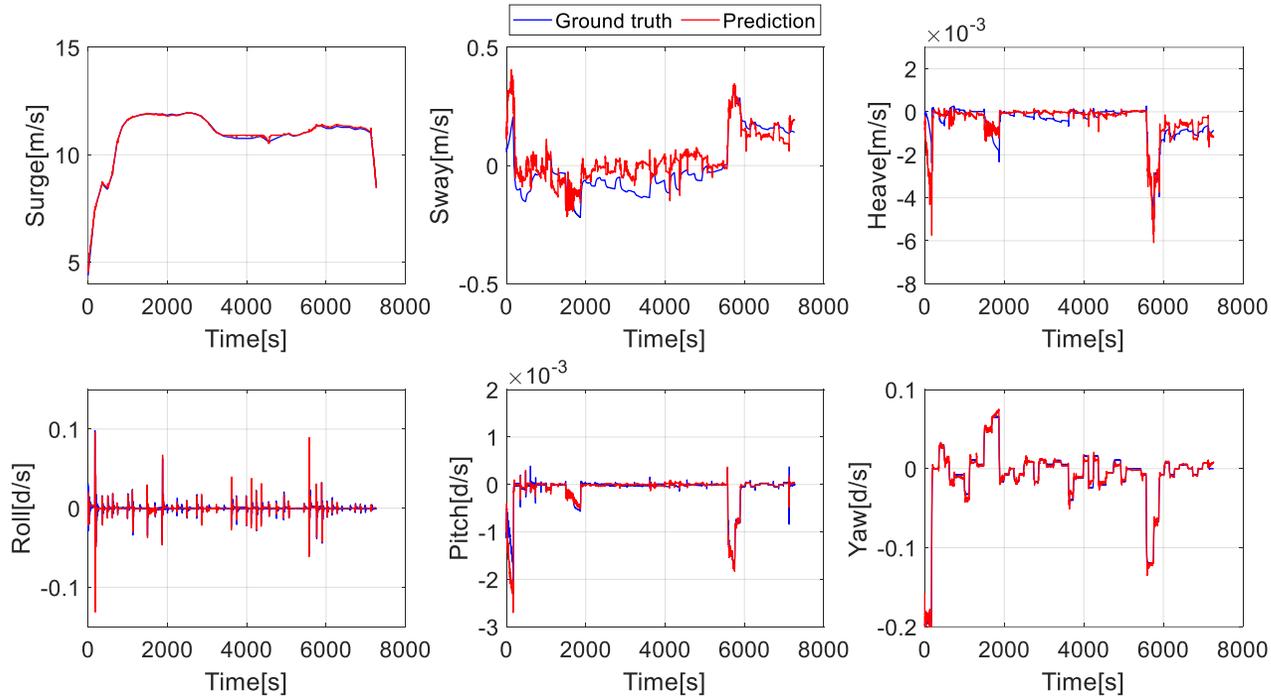
□ Model training and validation

- Operational conditions and maneuvering commands set as inputs
- Ship motions set as outputs
- 80% of data used for training the model
- 20% of data used for validation

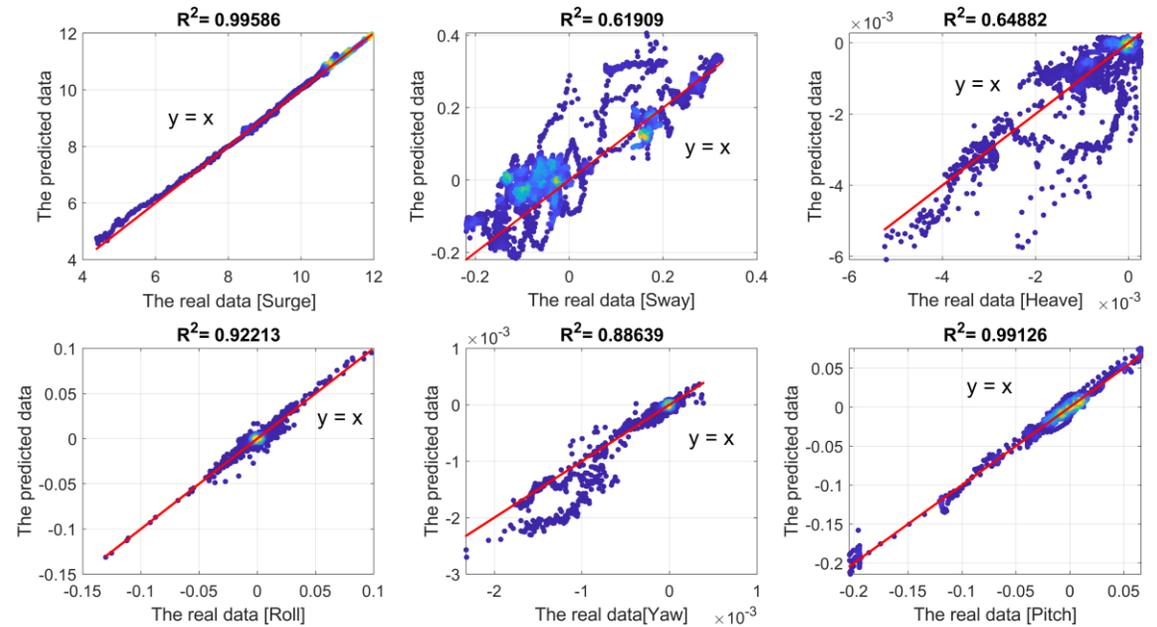


Results of layer 2 (model training / validation)

Comparison of real / predicted ship motions



Performance evaluation using R^2 value



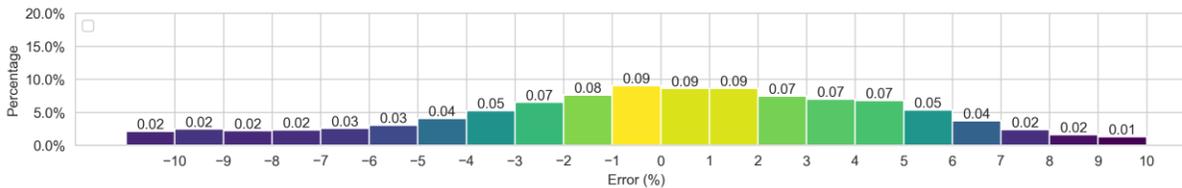
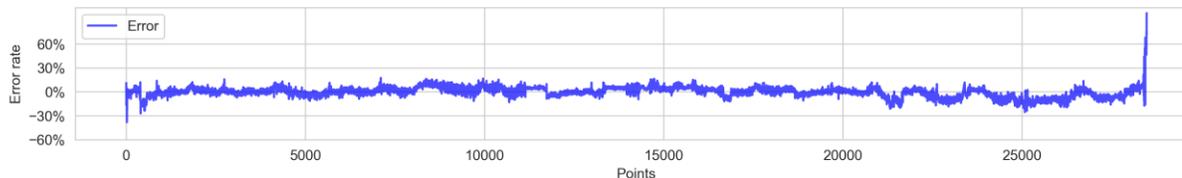
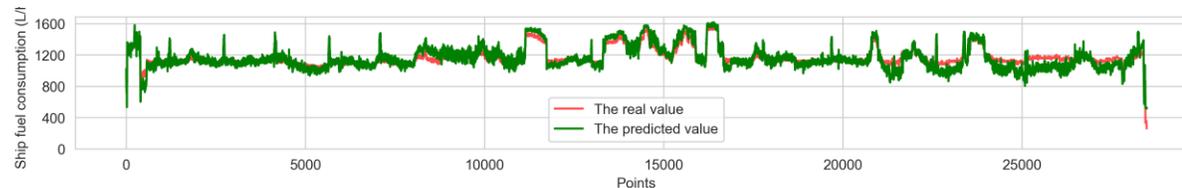
- R^2 values for surge, roll, and pitch predictions exceeded 0.9
- R^2 values for sway and heave predictions are 0.62 and 0.65

	Error	Surge	Sway	Heave	Roll	Yaw	Pitch
Transformer	MAE	0.0529	0.0599	0.0003	0.001	0.0001	0.0026
	RMSE	0.0745	0.0734	0.0004	0.0021	0.0001	0.0037

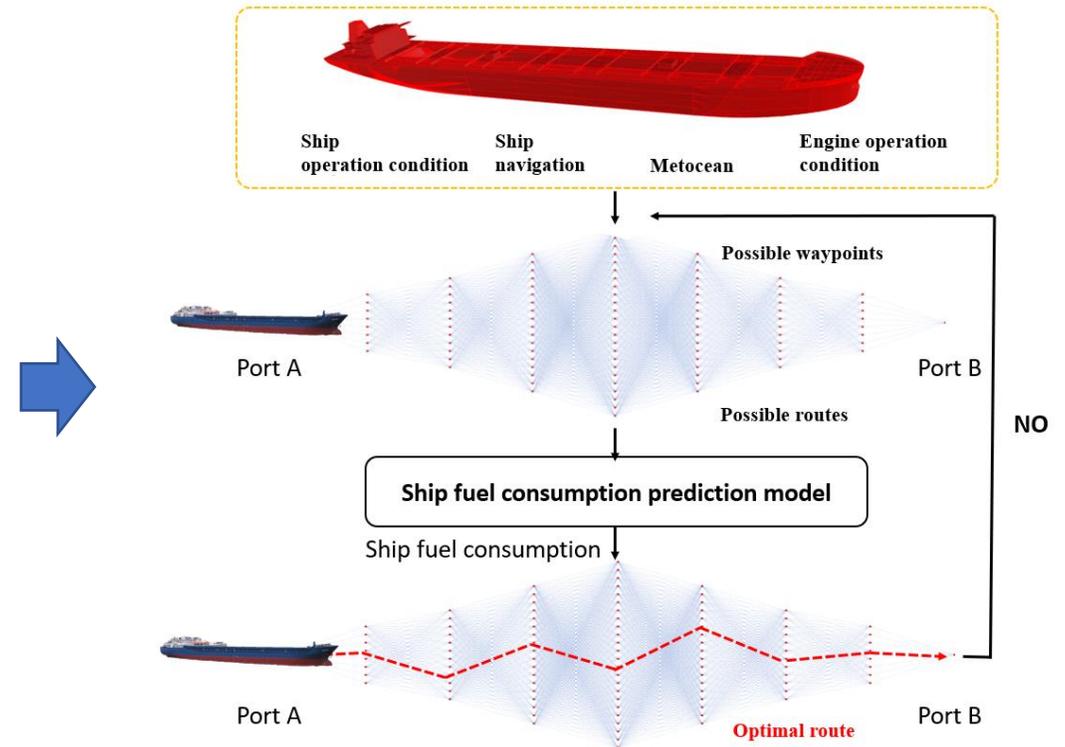
Applications on sustainable ship operations

❑ Ship fuel consumption prediction for whole voyage

	Condition	Departure / destination	Voyage lengths
Voyage 1	Laden condition	Vancouver / Yantai	7223.90 nm



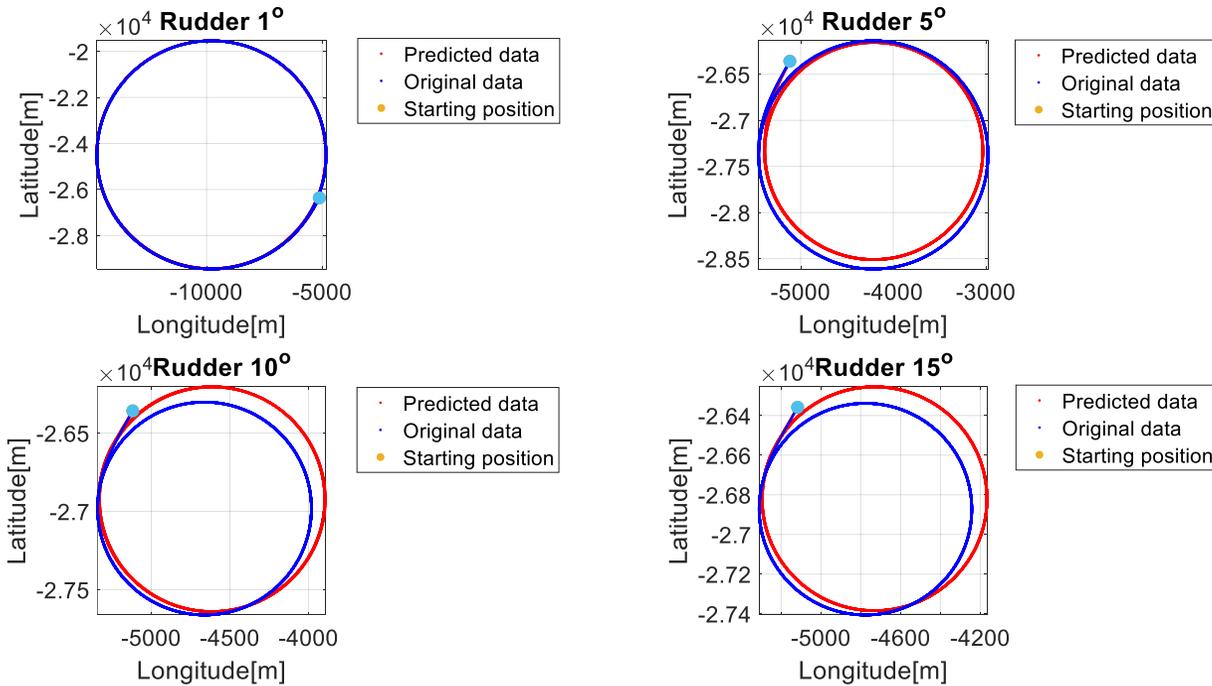
- The ship digital twin can accurately capture ship energy system for ship fuel consumption in real conditions



- The iterations within the optimization process can help
 - ✓ identify of the most efficient ship operations
 - ✓ reduce fuel consumption.

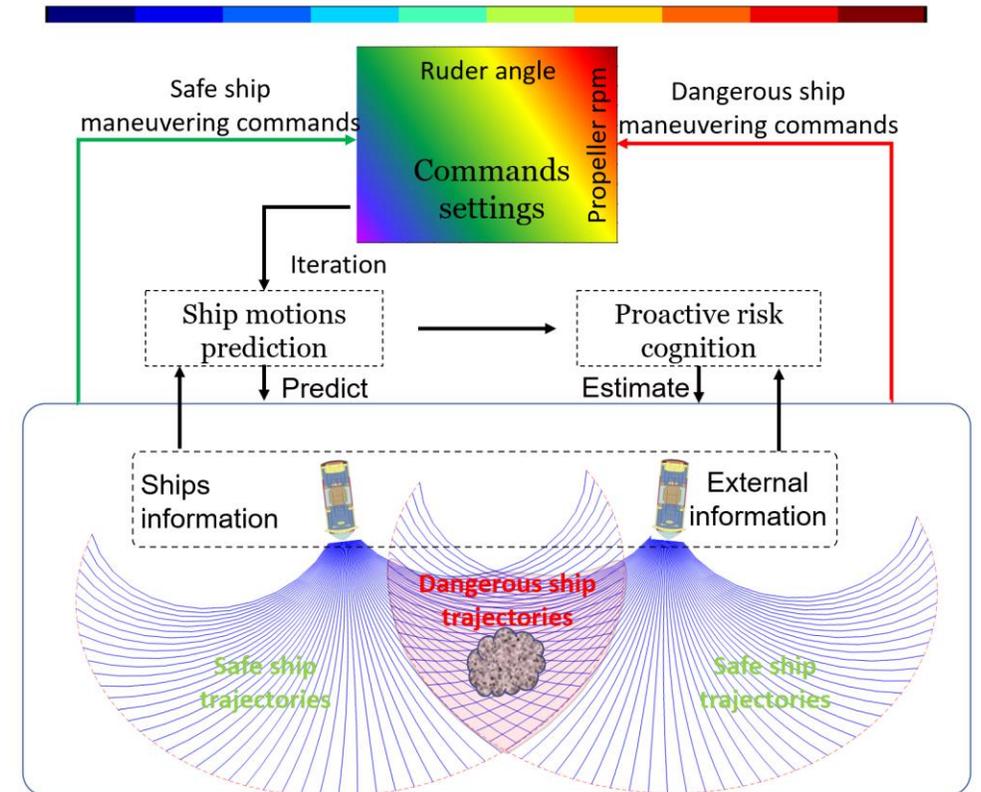
Applications on safe ship operations

❑ Ship turning circle prediction



- The trained deep learning neural network can accurately capture ship motion dynamics in real conditions

❑ Safe ship operations



- Ship maneuvering commands can be determined for proactive navigation avoidance

Conclusions

AI based ship digital twins may contribute to safer and sustainable ship operations



Prediction of ship motion dynamics reflecting hydro- meteorological conditions (i.e., wind, wave, currents, etc.)



Estimation of ship fuel consumption of whole long voyage



Optimization of ship operations in real operational conditions



Intelligent navigation monitoring and decision support systems

Thank you!

Questions?

