Safe Motion Prediction with Physics and Deep Learning

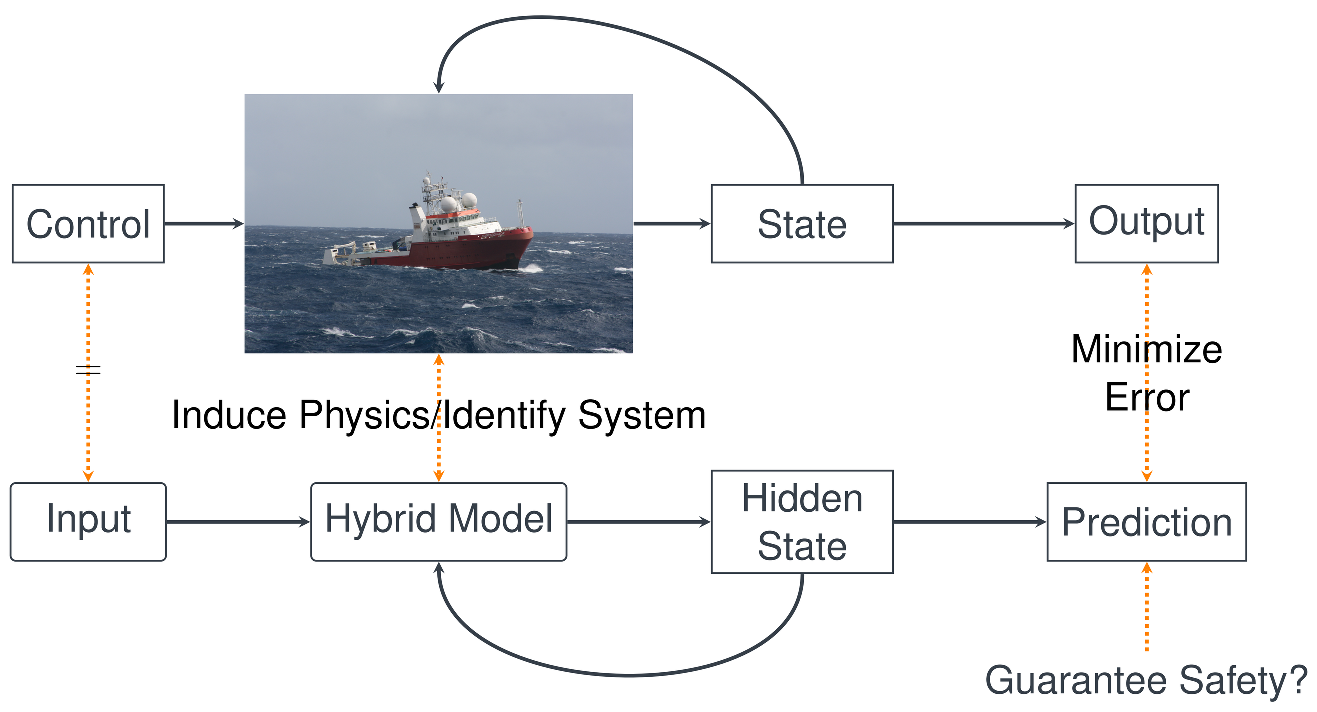
University of Stuttgart
Cluster of Excellence in Data-integrated Simulation Science

Project Coordinator: Prof. Dr. Steffen Staab
Institute for Parallel and Distributed Systems
Analytic Computing

Alexandra Baier

PN4

Physics-Informed System Identification



⇒ Deep neural networks achieve high in-distribution accuracy
⇒ Physics-informed networks improve generalizability
⇒ How to ensure predictions fulfill safety criteria?
Guarantee bounds on predictions

Physics Residual-Bounded LSTM

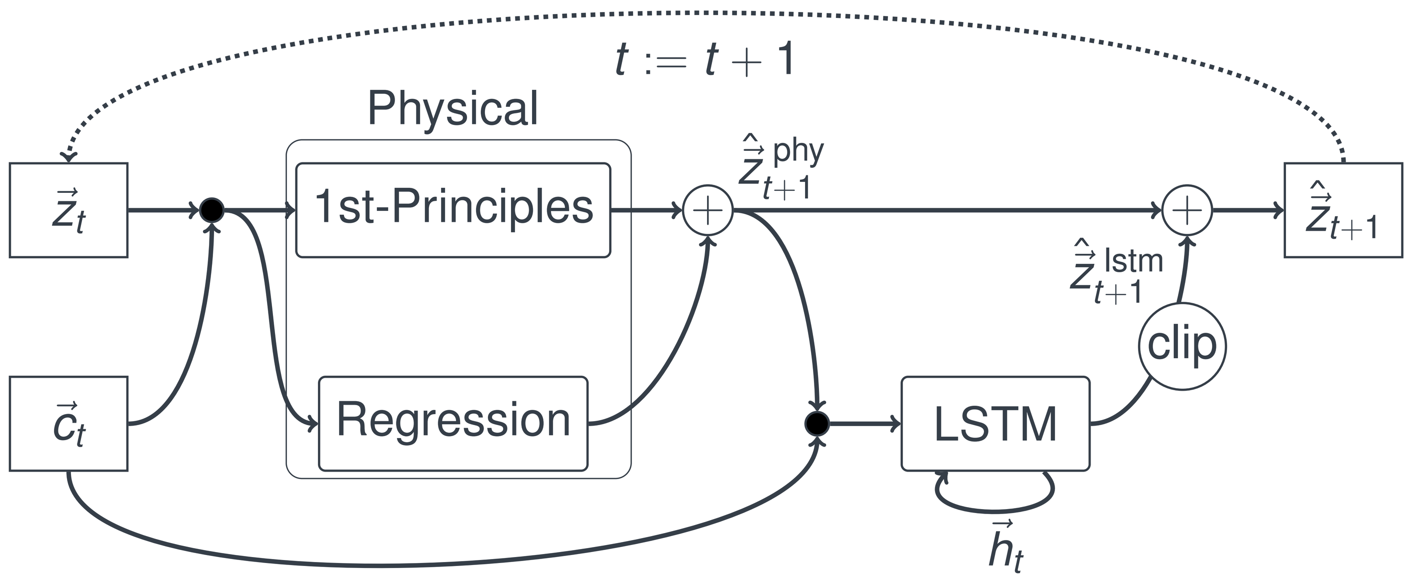


Figure 1: The proposed hybrid architecture consists of a physical model (regression and first-principles) and an LSTM. Concatenation of vectors is represented by a black circle. The $+$-operators correspond to a vector addition.

Guarantees

Predictions of our approach are bounded over all time steps, when
- LSTM predictions are clipped to a constant threshold
- Physical model is UBIBS stable

⇒ Computation of the model's reachable set enables safety verification

Results

Table 1: Root mean squared error for each state variable and trajectory.. NARX and LSTM are baselines. Other models are physics residual-bounded LSTMs (PRBL). The best and second-best score per column are marked in **bold** and ***bold+italics*** respectively.

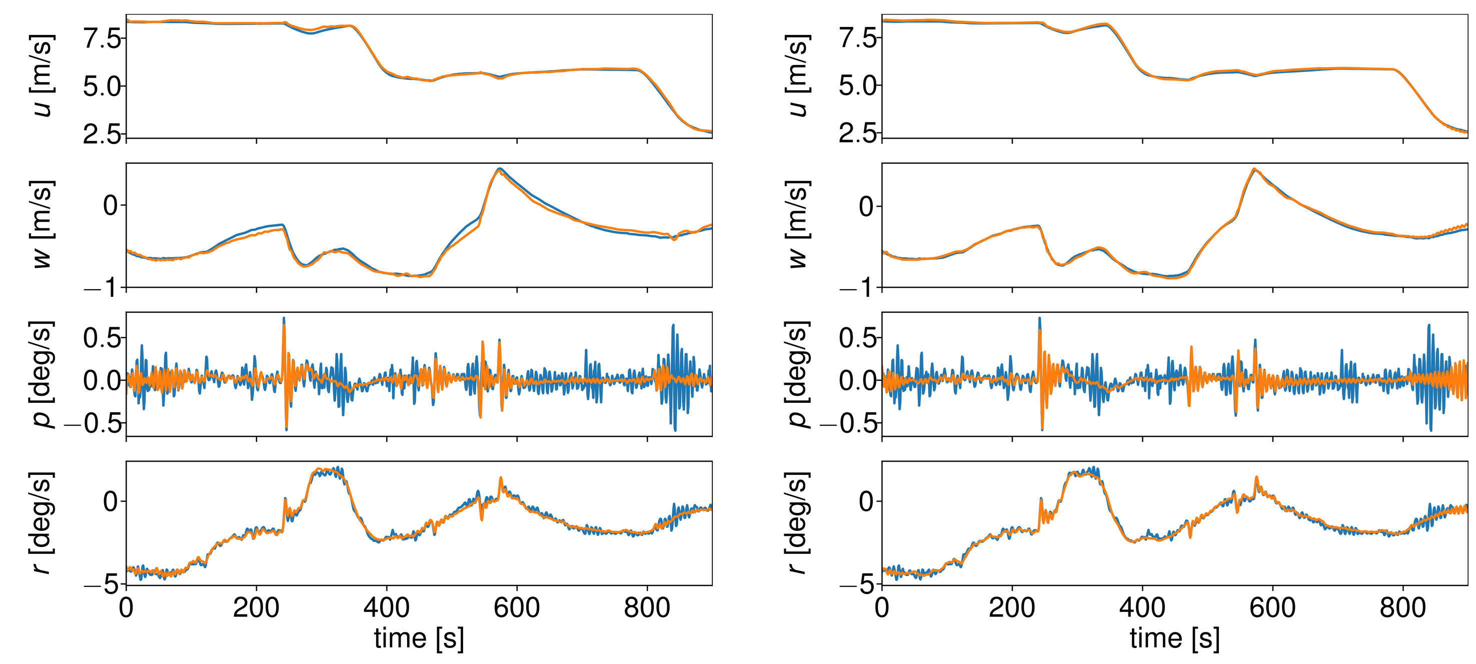
Model	u m/s	w m/s	p rad/s	r rad/s	ϕ rad	Trajectory m (95%)
NARX	0.135	0.099	**0.0049**	0.0035	0.0085	604 ± 5
LSTM	0.085	***0.054***	***0.0056***	***0.0020***	**0.0070**	290 ± 3
PRBL-Lin	0.077	**0.048**	0.0057	**0.0018**	**0.0070**	***273 ± 3***
PRBL-Min+Lin	***0.070***	0.055	0.0060	***0.0020***	0.0074	**269 ± 3**
PRBL-Pro+Hyd	**0.068**	0.063	0.0058	0.0021	0.0078	285 ± 3

Code & Data

Code @ GitHub/deepsysid

Dataset @ DaRUS - SimTech PN 4-7

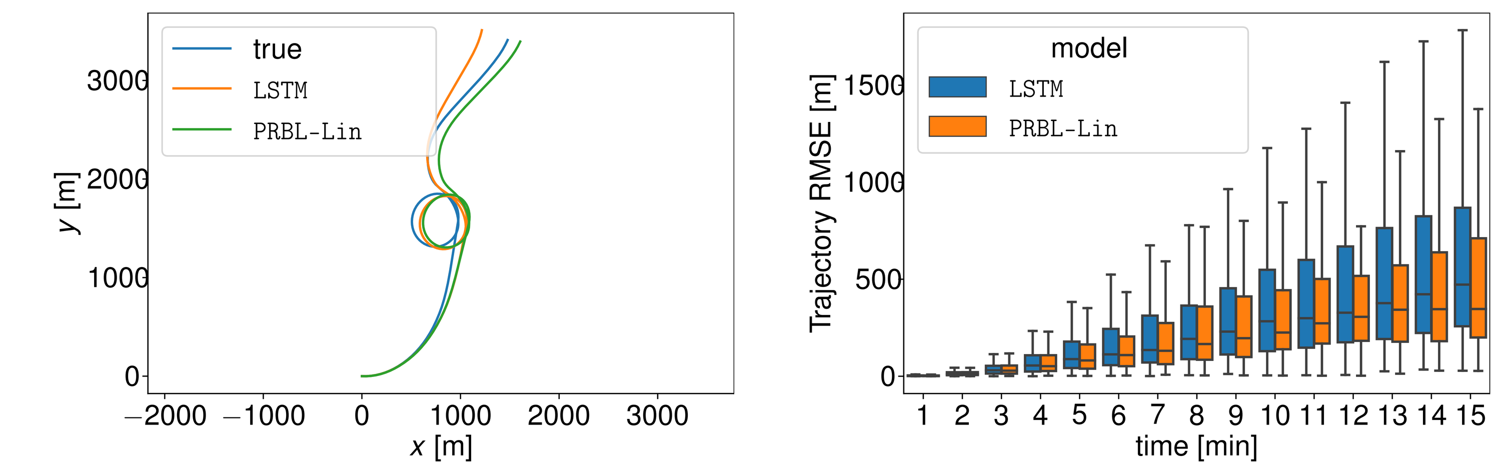
State Prediction



(a) LSTM **(b)** Physics Residual-Bounded LSTM

Figure 2: Ship state prediction over 900 seconds. Prediction in orange. True in blue.

Trajectory Prediction



(a) Trajectory is computed from previously predicted states (see above). **(b)** Distribution of trajectory error per minute.

Figure 3: Trajectory prediction over 900 seconds.

Reachability

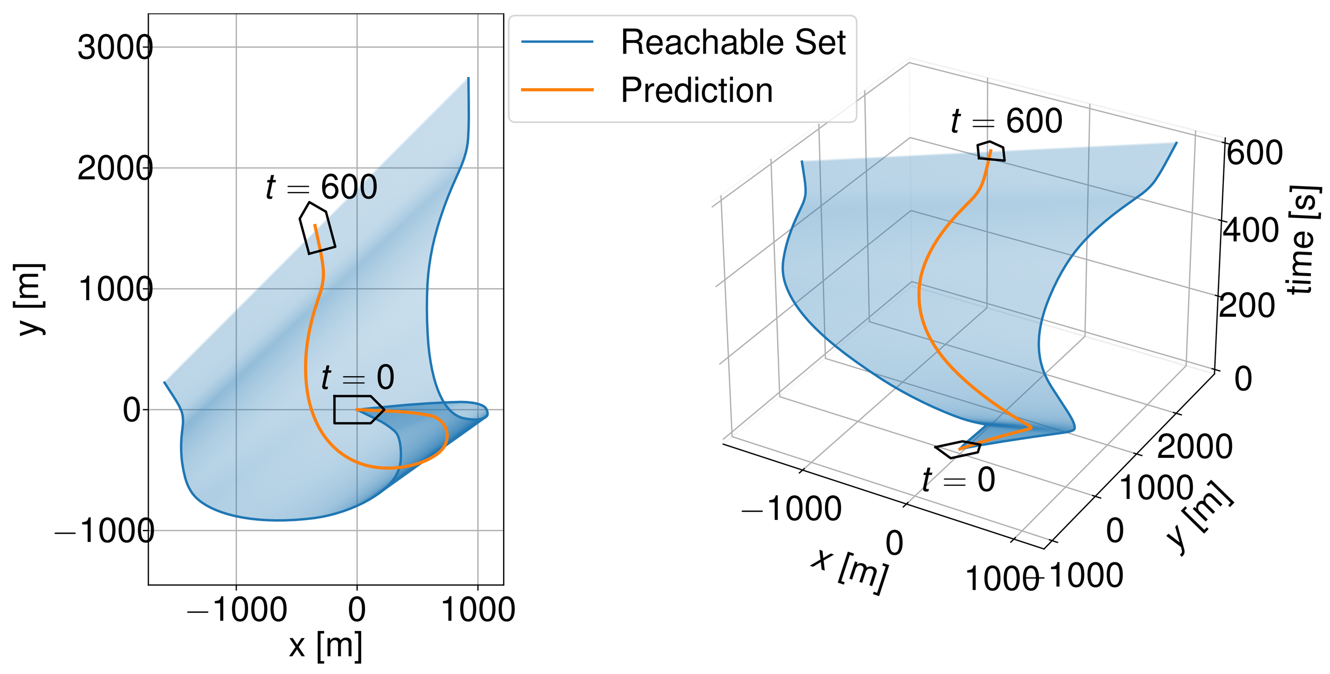


Figure 4: Trajectory and corresponding reachable set is predicted by PRBL-Lin. (left) Trajectory in two-dimensions. (right) Same trajectory on x- and y-axes with time on z-axis.

Notation

$\vec{c}_t$ = control vector
$\vec{z}_t = \left[u_t\ v_t\ p_t\ r_t\ \phi_t\right]$ = state vector
u = surge velocity (along x-axis), v = sway velocity (along y-axis),
p = roll rate (around x-axis), r = yaw rate (around z-axis), ϕ = roll angle

PRBL = Physics Residual-Bounded LSTM
Lin = Linear time-invariant regression component
Hyd = Regression component including non-linear hydrodynamic terms
Min = Minimal first-principles component (mass, inertia)
Pro = First-principles component including propulsion

References

[1] A Baier, Z Boukhers, and S Staab.
Hybrid Physics and Deep Learning Model for Interpretable Vehicle State Prediction.
CoRR, 2022.

[2] A Baier, S Staab, D Aspandi, and Z Boukhers.
Physics Residual-Bounded LSTM for Safe Vehicle State Prediction.
Submitted: IEEE Trans. on Neural Networks and Learning Systems.

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