Van der Pol-informed Neural Networks for Multi-step-ahead Forecasting of Extreme Climatic Events

Anurag Dutta[1], Madhurima Panja[2], Uttam Kumar[2], Chittaranjan Hens[3], Tanujit Chakraborty[4]

[1]GCETTS, [2]IIIT Bangalore, [3]IIIT Hyderabad, India, [4]Sorbonne University

OVERVIEW: Building Physics-Informed Neural Networks for accurate forecasting of extreme climatic events using a physics-informed differential learning approach for mitigating the impacts of severe climatic disasters.

MOTIVATION:

- Modeling the nonlinear dynamical systems of extreme climatic phenomena is an open scientific challenge.
- Physics-based dynamical systems provides an efficient mechanism for understanding the inherent dynamics of the chaotic systems.
- Machine learning approaches are vital for modeling the long-term system trajectories from a data-centric perspective without particular emphasis on the physical laws governing the system.

CONTRIBUTIONS:

- Modeling the temporal evolution of real-world extreme climatic events by integrating the physical knowledge into the data-driven forecasting mechanism.
- The dynamics of the Van der Pol oscillatory system is infused with the data-centric long-short term memory (LSTM) model using transfer learning and a physics-informed loss function.
- Enhancing the modeling and forecasting capabilities of the LSTM framework for nonlinear dynamical systems.
- Reducing the computational complexity and data requirements of the LSTM model

METHODOLOGY:

VPINN leverages the transfer learning approach and physics-based regularized loss function to incorporate the dynamics of the physical laws into the data-driven forecasting model.

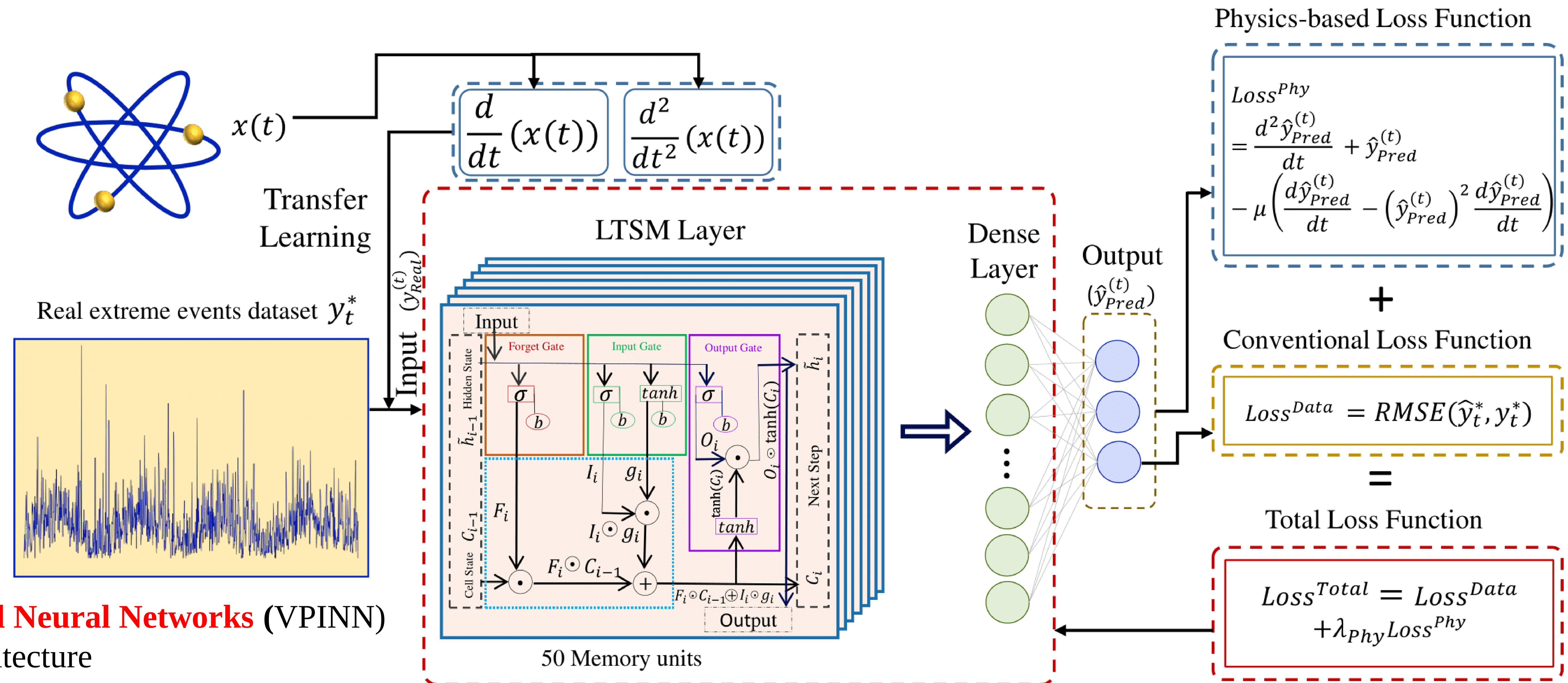

Fig: Van der Pol-informed Neural Networks (VPINN) Architecture

FORECASTING: BENCHMARK COMPARISON

Model		SES		LSTM		RCN		Prophet		Bi-LSTM		NBeats		VPINN		IMP
Metric		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Turkey	ST	0.555 (0.00)	0.506 (0.00)	2.912 (0.08)	2.014 (0.02)	0.576 (0.12)	0.381 (0.10)	0.576 (0.10)	0.432 (0.01)	3.630 (0.10)	3.522 (0.12)	0.573 (0.01)	0.431 (0.10)	**0.514** (0.01)	**0.360** (0.01)	82.3%
SW	LT	1.150 (0.00)	1.108 (0.00)	2.752 (0.01)	1.879 (0.01)	1.332 (0.99)	0.617 (0.52)	0.553 (0.08)	0.389 (0.05)	3.544 (0.08)	3.429 (0.15)	0.552 (0.08)	0.504 (0.15)	**0.446** (0.01)	**0.323** (0.01)	83.7%
Delhi	ST	14.75 (0.00)	14.52 (0.00)	8.026 (0.83)	6.285 (0.89)	32.95 (5.31)	29.83 (6.17)	6.079 (2.72)	4.872 (1.10)	7.982 (0.81)	6.693 (1.23)	5.712 (1.00)	**4.648** (0.67)	**5.604** (0.28)	4.863 (0.39)	30.2%
WS	LT	8.040 (0.00)	7.532 (0.00)	6.748 (0.92)	4.812 (0.85)	36.88 (8.92)	26.38 (5.38)	6.726 (1.21)	5.258 (0.97)	6.769 (1.00)	5.167 (0.95)	6.749 (1.01)	4.914 (0.45)	**6.673** (0.21)	**4.369** (0.20)	1.11%
El Niño	ST	18.08 (0.00)	18.06 (0.00)	22.38 (1.05)	22.22 (1.61)	5.352 (2.01)	4.182 (1.28)	**2.346** (1.00)	**1.924** (0.99)	23.32 (1.27)	23.26 (0.95)	2.934 (0.18)	2.669 (0.98)	7.471 (0.43)	7.208 (0.48)	66.6%
SST	LT	22.65 (0.00)	22.55 (0.00)	19.82 (4.64)	19.69 (1.45)	15.15 (3.99)	12.19 (2.31)	7.201 (1.27)	6.841 (1.56)	21.57 (1.98)	21.44 (1.46)	7.273 (1.72)	6.385 (0.55)	**6.016** (0.34)	**5.426** (0.35)	69.6%
Madrid	ST	63.09 (0.00)	61.01 (0.00)	46.47 (2.52)	44.28 (2.47)	26.98 (3.01)	24.49 (9.48)	28.52 (2.16)	25.79 (1.99)	48.79 (1.98)	46.72 (1.37)	27.73 (1.99)	22.61 (2.89)	**26.14** (0.01)	**22.04** (0.00)	43.7%
Humidity	LT	67.60 (0.00)	65.84 (0.00)	52.78 (2.89)	50.83 (1.89)	61.90 (1.76)	52.92 (1.95)	34.89 (2.20)	**26.89** (2.09)	54.23 (2.10)	52.35 (2.51)	**31.64** (1.54)	27.69 (2.74)	35.76 (0.01)	32.75 (0.01)	32.2%
Philippines	ST	17.14 (0.00)	16.83 (0.00)	25.01 (1.74)	24.68 (1.85)	18.78 (2.97)	16.78 (1.89)	14.57 (1.78)	13.98 (1.09)	26.06 (1.30)	25.76 (1.99)	13.95 (2.01)	13.56 (2.00)	**13.89** (0.99)	**13.29** (2.30)	44.4%
Temp	LT	16.57 (0.00)	16.12 (0.00)	26.04 (1.92)	25.70 (2.08)	17.05 (2.08)	15.16 (2.01)	18.25 (1.99)	17.86 (0.18)	26.46 (2.10)	26.13 (2.23)	20.44 (2.27)	19.69 (1.92)	**12.94** (1.25)	**12.56** (2.01)	50.3%

Table : Short-term and long-term forecasting performance (RMSE and MAE) of the proposed VPINN model in comparison to the state-of-the-art forecasting techniques (best results are **highlighted**).

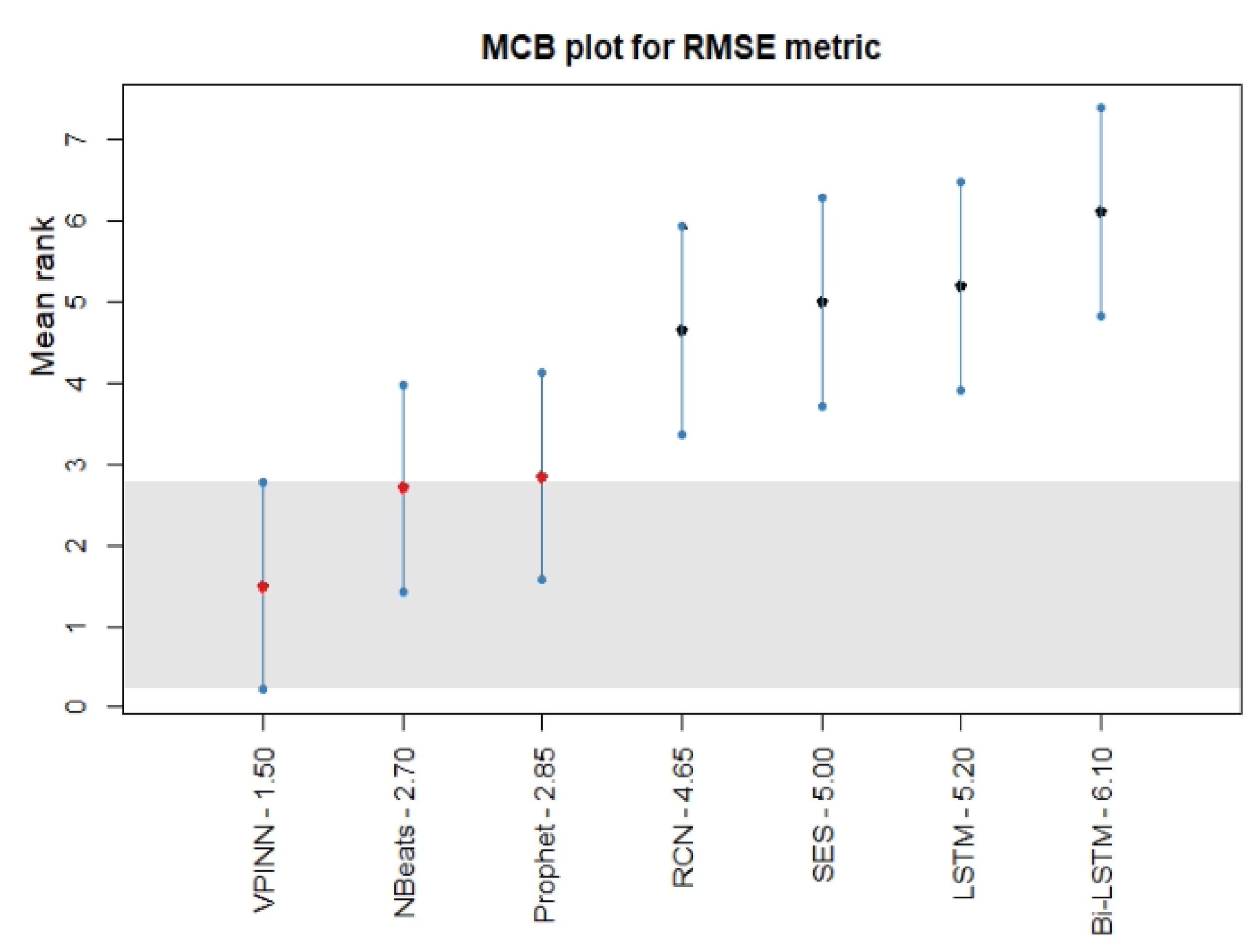

Fig: Visualization of the multiple comparison with the best (MCB) analysis w.r.t. RMSE. The Y-axis of the plot shows the average rank and the X-axis represents corresponding model.

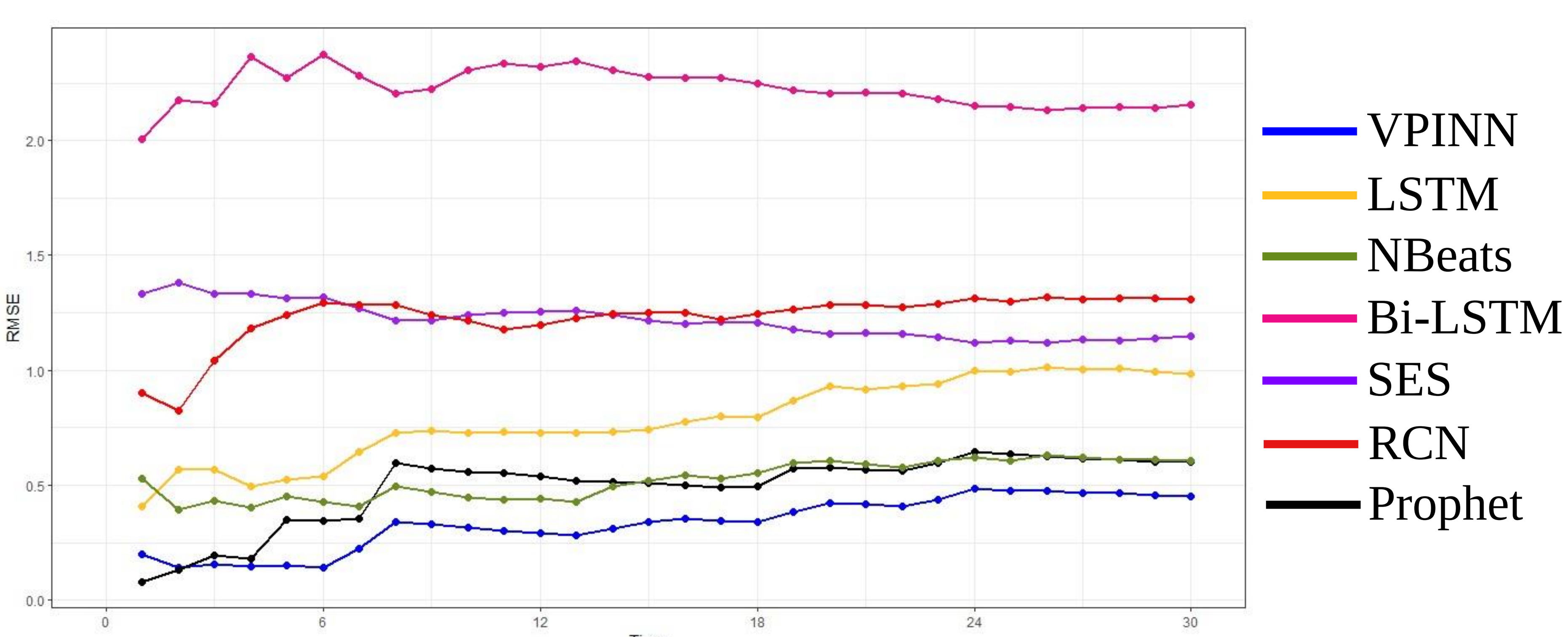

Fig: RMSE (error metric) values of the proposed model and the state-of-the-art for Turkey Seismic Waves dataset at each forecast steps.

CONCLUSIONS

- VPINN enhances forecastability through a combination of transfer learning and a physics-informed loss function.
- The modeling capabilities of the VPINN framework show promise for developing and refining additional physics-guided forecasters capable of handling the complex geophysical turbulence of extreme climatic events.

Code Data

tanujit.chakraborty@sorbonne.ae

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