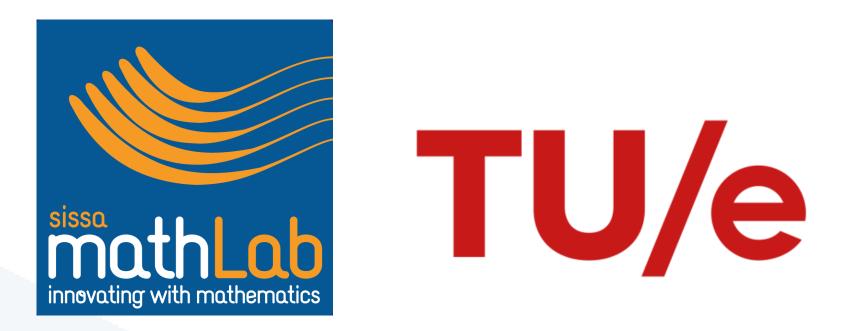
# A Numerical Proof of Shell Model **Turbulence Closure**

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#### **Results (1): Eulerian Structure Functions Introduction and Motivations** In this work we define a Subgrid Closure The the $p^{th}$ order Eulerian structure model that, employed in a Large Eddy Simfunctions, with $p = 1, \dots, 10$ , can be ulation approach, exhibits correct scaling laws FRM computed as: in high order Structure Functions, encom- $10^{0}$ LSTM-LES passing intermittent effects and energy cascade $S_n^p = \langle |u_n|^p \rangle.$ (1)dynamics. $10^{-2}$ Due to the massive amount of data needed to On the left, results for the Fully Rereach converged statistics of high order statisti-

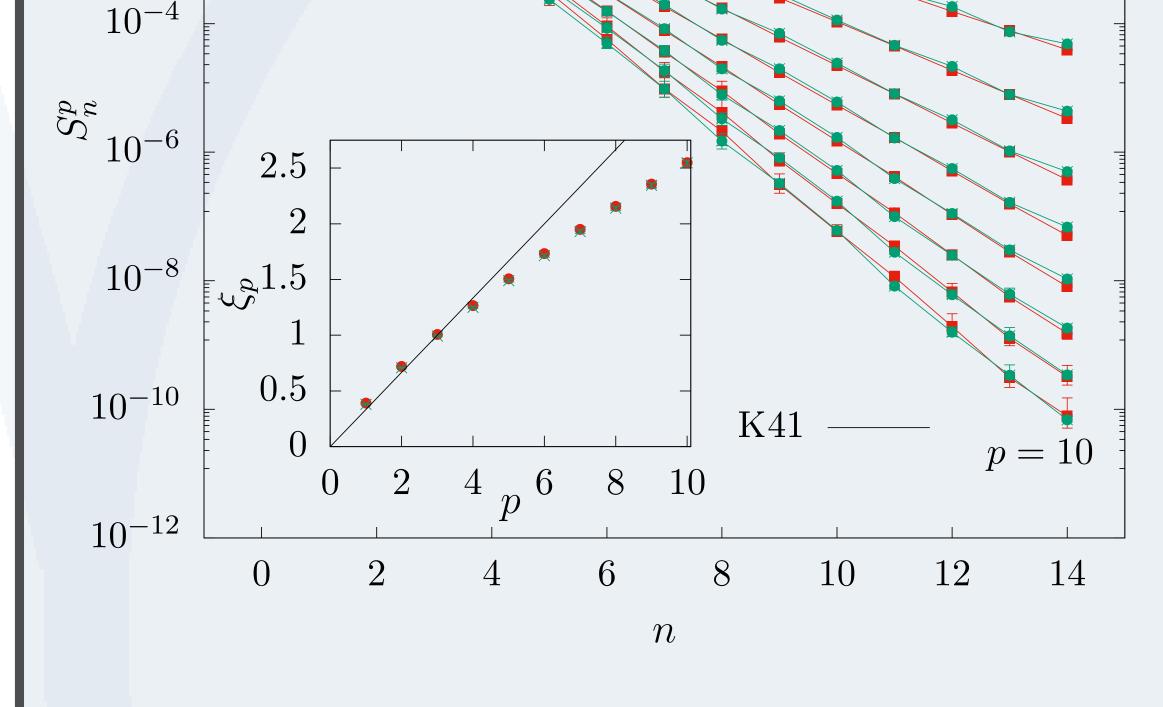
solved Model (FRM) and our LSTM-

cal moments, we consider the setting of **Shell** Models of Turbulence [1].

Our method employs a custom-made **Deep** Learning architecture comprising a Runge-Kutta integration scheme for the large scales of turbulence, augmented with a **Recurrent Ar**tificial Neural Network.

#### **Shell Models of Turbulence**

Shell models mimic the dynamics of Homogeneous Isotropic Turbulence in Fourier **space** via a (small) number of scalars  $u_n$ , n = $0, 1, \ldots, N$ , whose magnitude represents the energy of fluctuations at representative logarithmically equispaced spatial scales (wavelength  $k_n = k_0 \lambda^n$ ).



**LES** model (shell index n on the x-axis).

In the inset, the values of the anomalous exponents,  $\xi_p$ ,  $S_n^p \propto k_n^{-\xi_p}$ , with the predictions from the **K41 theory**.

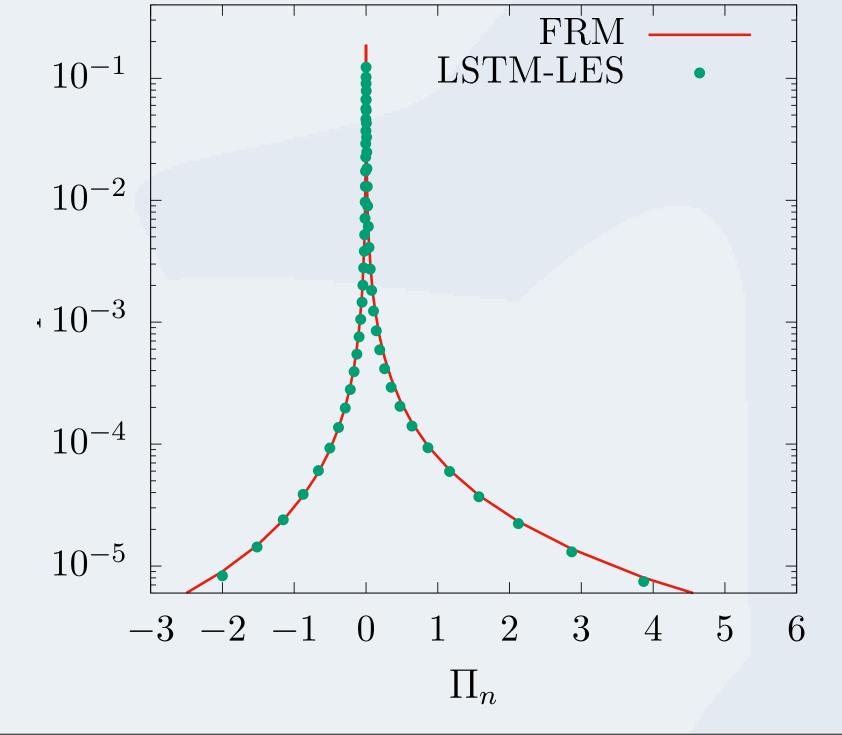
Find in [3] results for high order Lagrangian structure functions, with specifications on statistical error bars.

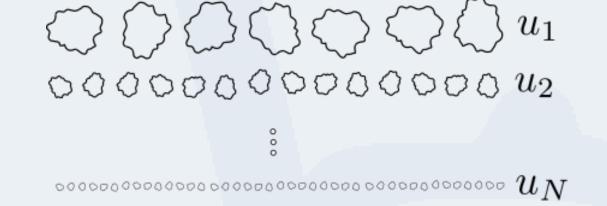
## Results (2): Pdf of Energy Fluxes

The convective fluxes at shell  $N_{cut}$  can be computed as |2|:

$$\Pi_{N_{cut}} = \frac{d}{dt} \sum_{n=0}^{N_{cut}} |u_n(t)|^2$$

On the right, the probability distribution function for both Fully Resolved Model (**FRM**) and our **LSTM-LES**.





The governing equations read:

 $\frac{du_n}{dt} = \epsilon \delta_{n,0} - \nu k_n^2 u_n +$ 

 $+F(u_{n-2}, u_{n-1}, u_n, u_{n+1}, u_{n+2})$ 

where  $F(\cdot)$  is a nonlinear coupling between the shells, mimicking the convective term of NSE.

A Large Eddy Simulation (LES) consists in evolving the large scales  $u^{<}$  above an (arbitrary) cutoff scale  $N_{cut} \ll N$  independently from the small (unresolved) scales  $u^>$ :

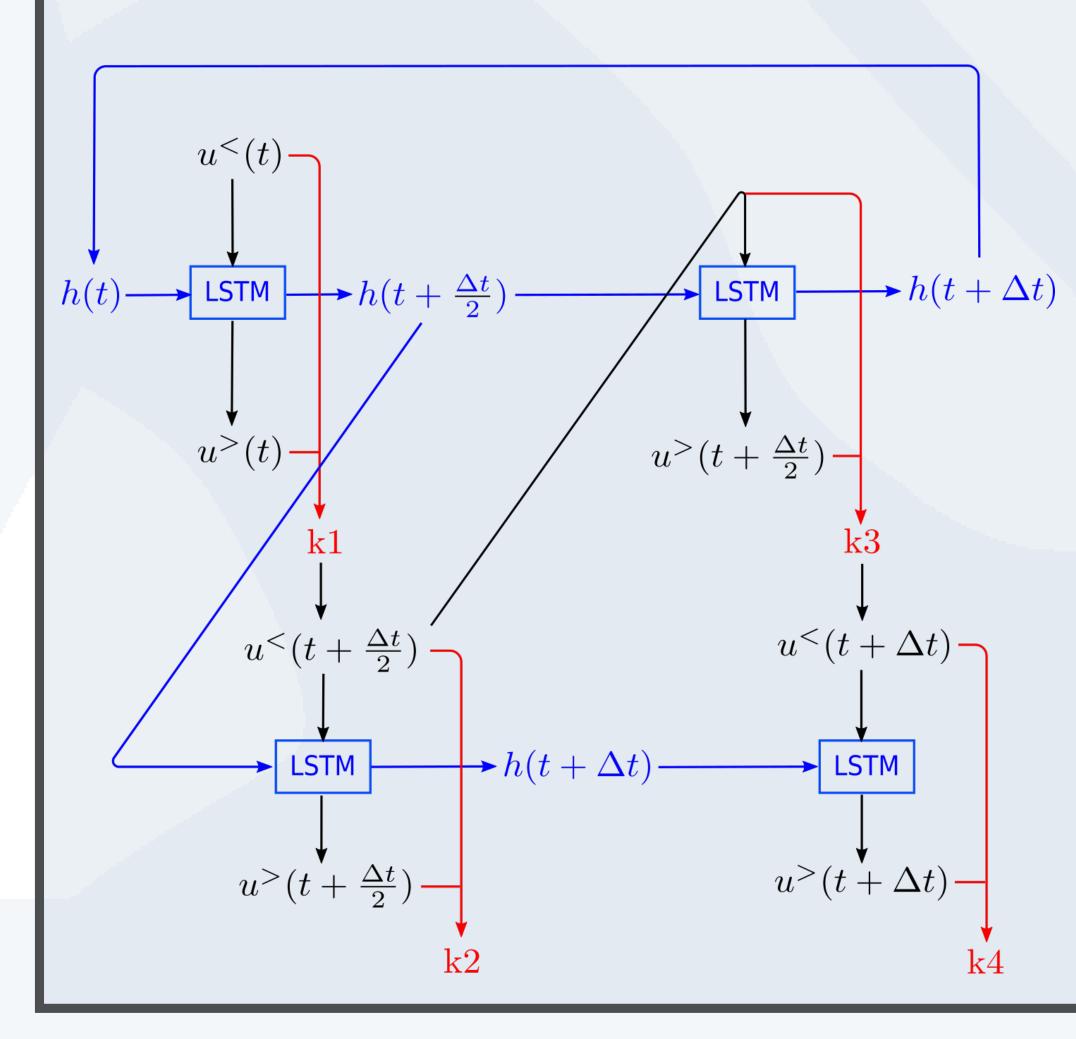
 $u = \{u_n\}_{n=0}^N = \begin{bmatrix} u^< \\ u^> \end{bmatrix} = \begin{bmatrix} \{u_n\}_{n=0}^{N_{cut}} \\ \{u_n\}_{n=N_{cut}}^N \end{bmatrix}$ 

The numerical values for the experiments:

Negative values of the flux correspond to **backscatter** events, correctly reproduced by our model.

Find in [3] results for **pdf of shell variables**.

### Methodology: LSTM-LES



Our method (LSTM-LES) consists of a modification of a Runge-Kutta integration scheme for the large scales:

$$u^{<}(t + \Delta t) = u^{<}(t) + \frac{\Delta t}{6}(\mathbf{k}_{1} + 2\mathbf{k}_{2} + 2\mathbf{k}_{3} + \mathbf{k}_{4})$$

The terms  $\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3$  and  $\mathbf{k}_4$  are computed by considering:

• the large scales  $u^{<}$ ;

• 
$$\nu = 10^{-12} \ (Re \approx 10^{12});$$

•  $N_{cut} = 15, N = 40.$ 

#### References

- [1] L. Biferale. Shell models of energy cascade in turbulence. Annu. Rev. Fluid Mech., 35(1):441-468, 2003.
- [2] L. Biferale, A. A. Mailybaev, and G. Parisi. Optimal subgrid scheme for shell models of turbulence. *Phys. Rev.* E, 95(4), Apr 2017.
- [3] G. Ortali, A. Corbetta, G. Rozza, and F. Toschi. A numerical proof of shell model turbulence closure. arXiv:2202.09289.

• the small scales  $u^>$ , computed by a Long-Short Term Memory (LSTM) Artificial Neural Network, taking as input the large scales  $u^{<}$  and a memory term h.

# **Conclusion and Outlook**

This work shows the capability of Machine Learning to capture complex multiscale dynamics and reproduce complex multi-scale and multi-time non-gaussian behaviors, opening up the possibility to use such methods to tackle turbulence modelling in Navier-Stokes Equations.