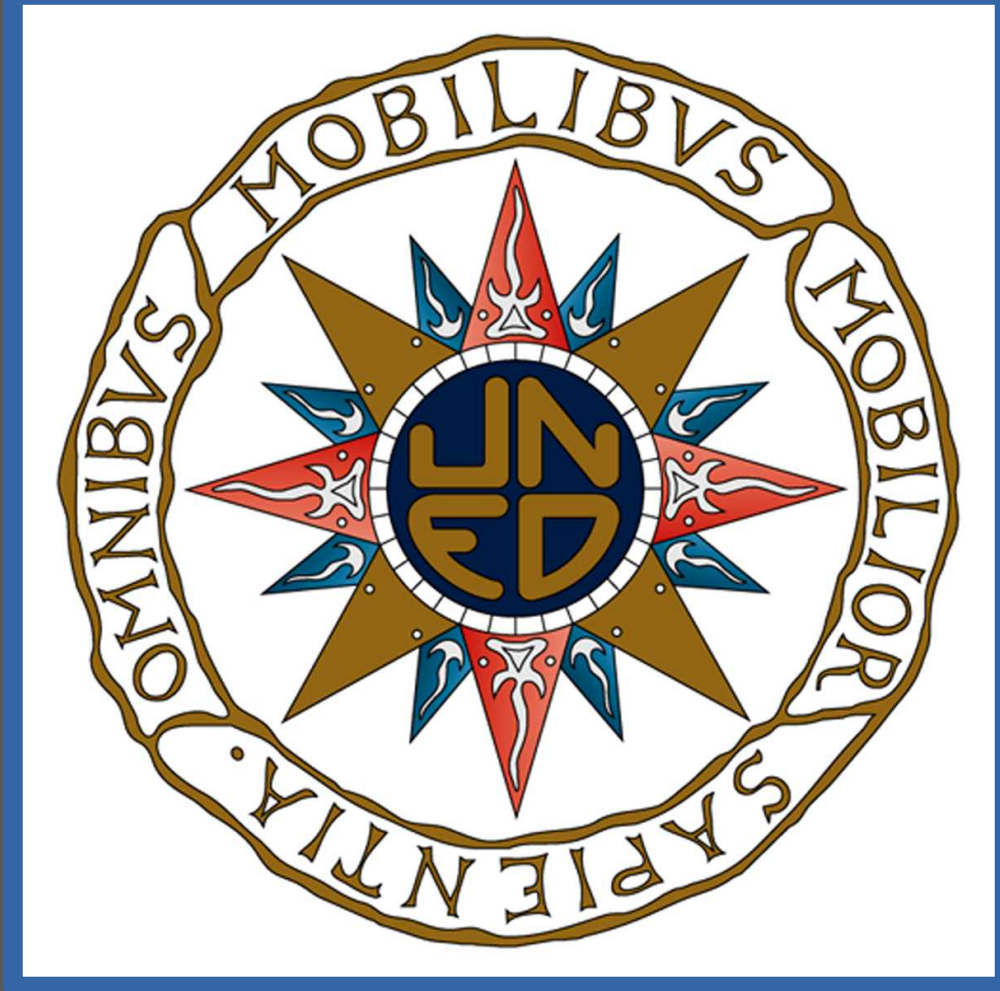




EIG²⁶

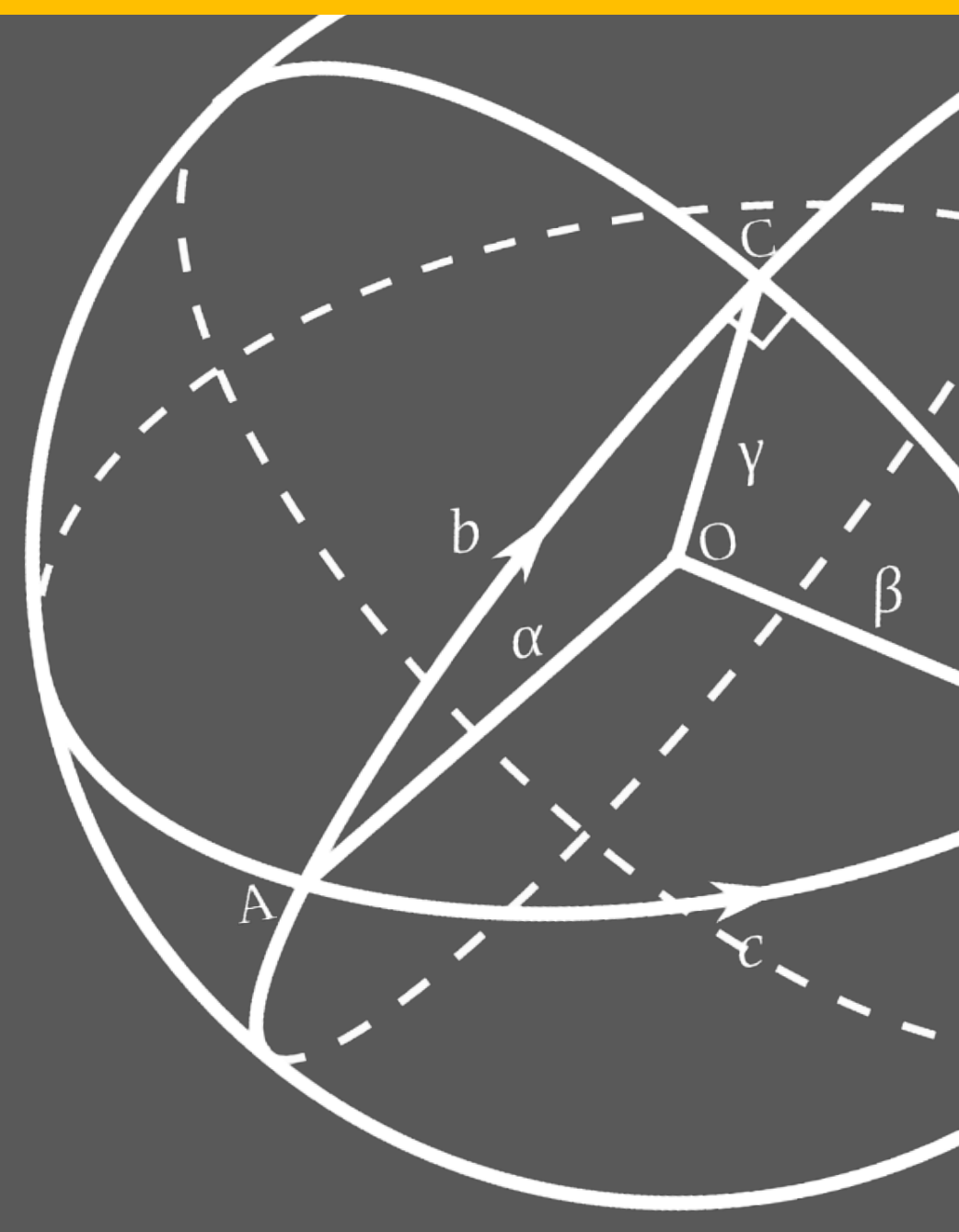
Innovative method for real-time volumetric pseudo-spherized cumuliform fluid dynamics simulation with deep RNNs

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ABSTRACT

As pointed out by Prof. F.J. Serón, «The pursuit of visually compelling and physically plausible real-time simulations of volumetric clouds remains a significant challenge in computer graphics». To address this challenge, we presented a novel method for real-time cumuli movement and transition based on a Recurrent Neural Network (RNN). Specifically, an LSTM, a GRU and an Elman RNN networks were trained on time-series data generated by a Jos Stam-based parallel Navier–Stokes fluid solver version. In the experiments, we obtained natural-looking behaviour for cumuli evolution and dissipation with excellent performance by the RNN fluid algorithm compared with that of classical finite-element computational solvers [1].

The core contributions of our research to the state of the art in cloud dynamics are:

- New method that replaces a Navier–Stokes fluid solver with a Recurrent Neural Network.
- Better constant real-time performance by the RNN fluids algorithm as compared to the previously reported methods.
- Natural cumuli behaviour in real-time irrespective of the 3D grid dimensions.
- Novel approach to simulate other complex physical processes with neural networks.

RELATED WORKS

Notably, some outstanding works on cloud dynamics paved the way for the research; however, there is no related work that employs a combined DNN with cumulative fluid dynamics for cloud movement simulation in computer graphics up to now. The most relevant related works are listed below:

- 1) The deep learning convolutional generative adversarial network (DCGAN) trained with captured cloud videos to generate interactive cloud maps on a real-time 3D application by Goswami et al. [3].
- 2) Cumuli, strati, and stratocumuli generation and realistic formations caused by changes in the atmosphere to simulate large-scale cloud super-cell clusters of cumulonimbus formations by Hädrich et al. [4].
- 3) Cumuliform cloud formation control by using a parameter-predicting convolutional neural network (CNN) by Zhang et al. [5].

OVERVIEW

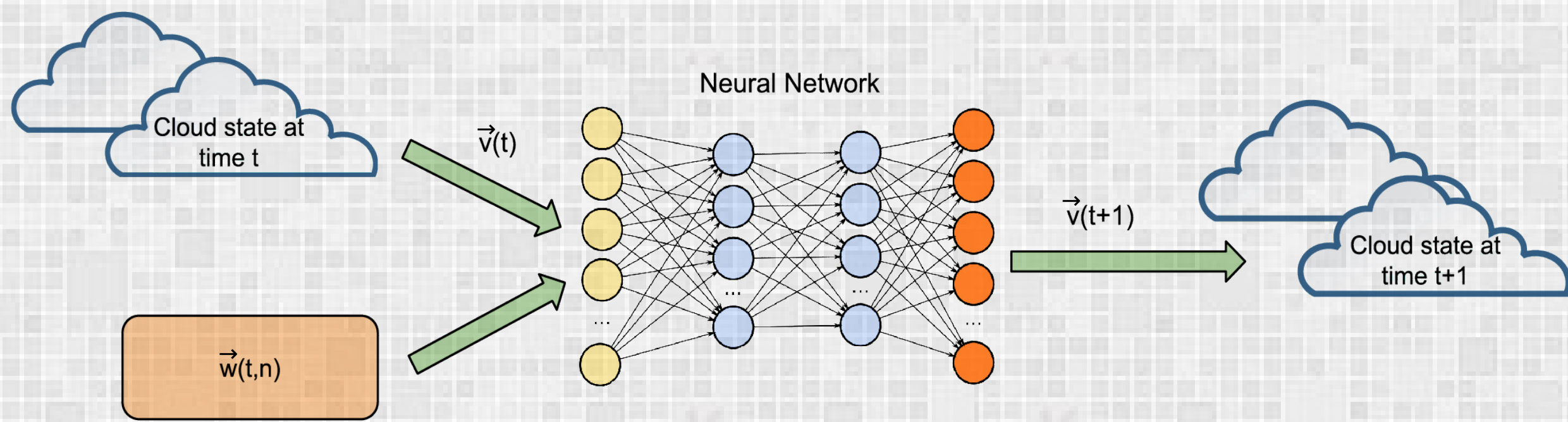


Figure 1. $\vec{v}(t)$ denotes the velocity vector of the cloud spheres at the current time instant, t . $\vec{w}(t,n)$ corresponds to the previous time vectors from time $t-n$, where n is an adjustable parameter corresponding to the window size (10). These two elements are concatenated, creating a notion of trajectory, and serve as input to the neural network that generates the predicted velocity vector for the next instant, $\vec{v}(t+1)$.

$$\nabla \cdot \vec{u} = 0$$

$$\frac{\partial \vec{u}}{\partial t} = -(\vec{u} \cdot \nabla) \vec{u} + \nu \nabla^2 \vec{u} + \vec{F}$$

Navier-Stokes density equation not required

Algorithm 1: Execution flow of the GPGPU parallel Navier–Stokes fluid solver simulator (CUDA).

```
1 while simulating do
2   forces3DGrid[i][j][k].u ← force_x           ▷ Apply wind force  $\forall i \forall j \forall k$ 
3   forces3DGrid[i][j][k].v ← force_y
4   forces3DGrid[i][j][k].w ← force_z
5   AddForce(grids,  $\delta t$ )                       ▷ Compute internal grids
6   Diffuse(grids, viscosity,  $\delta t$ )
7   Project(grids)
8   Advect(grids,  $\delta t$ )
9   Update forces3DGrid
10  Synchronize threads
11  for  $t \leftarrow 0 < \text{number of spheres}$  do
12     $x \leftarrow \text{sphereCenter}[t].x + M/2$        ▷ Change reference system
13     $y \leftarrow \text{sphereCenter}[t].y + N/2$ 
14     $z \leftarrow \text{sphereCenter}[t].z + O/2$ 
15     $\text{sphereCenter}[t].x += \text{forces3DGrid}[x][y][z].u$ 
16     $\text{sphereCenter}[t].y += \text{forces3DGrid}[x][y][z].v$ 
17     $\text{sphereCenter}[t].z += \text{forces3DGrid}[x][y][z].w$ 
```

MATERIAL AND METHODS

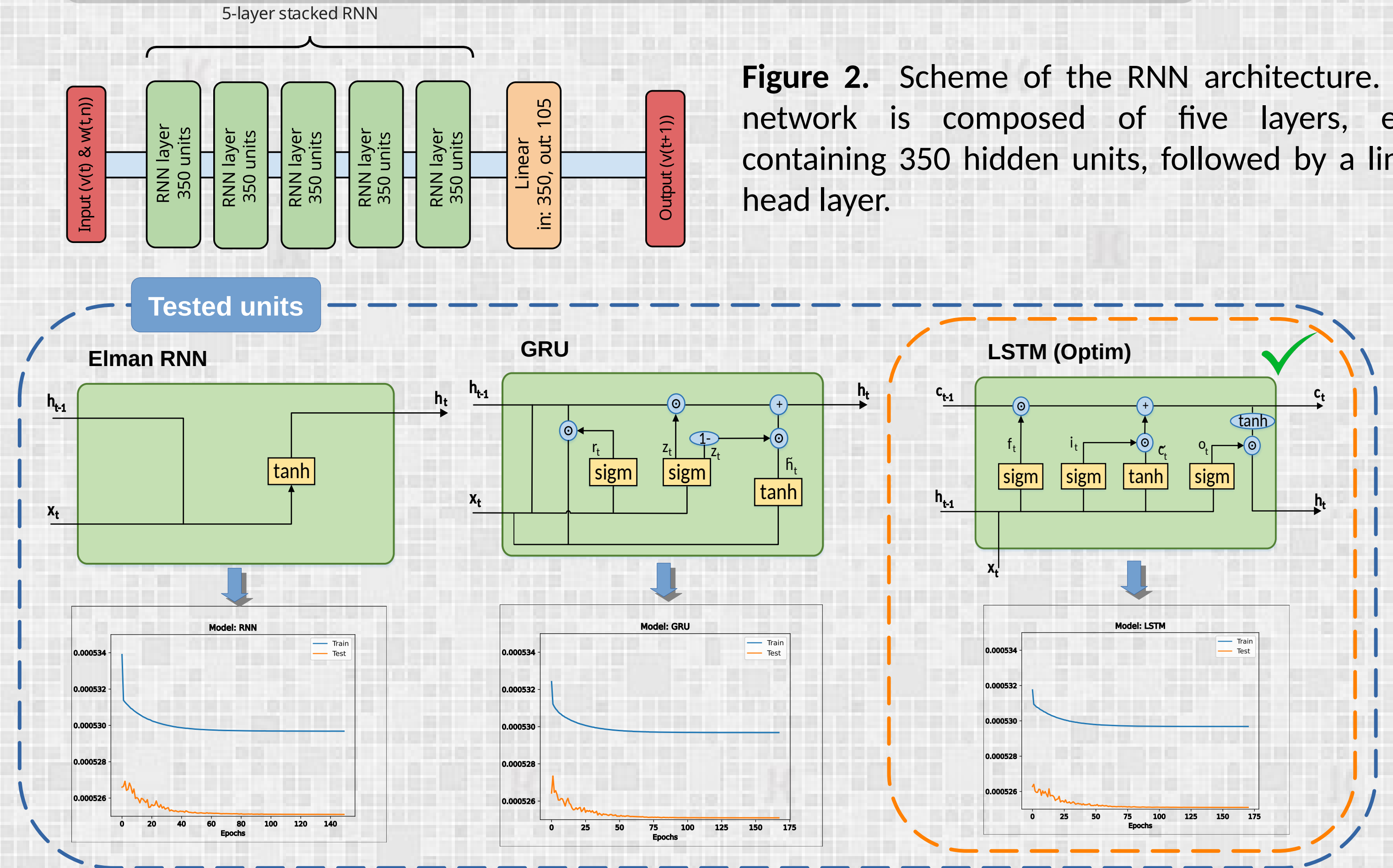


Figure 2. Scheme of the RNN architecture. The network is composed of five layers, each containing 350 hidden units, followed by a linear head layer.

RESULTS

	Elman RNN	LSTM	GRU	ARIMA
Test MSE	0.000526	0.000525	0.000525	0.00815

Table 1: Mean Squared Error (MSE) metrics for the different methods used. LSTM produced the best results.

Complexity: $O(L(4h(d + 3 + h)))$

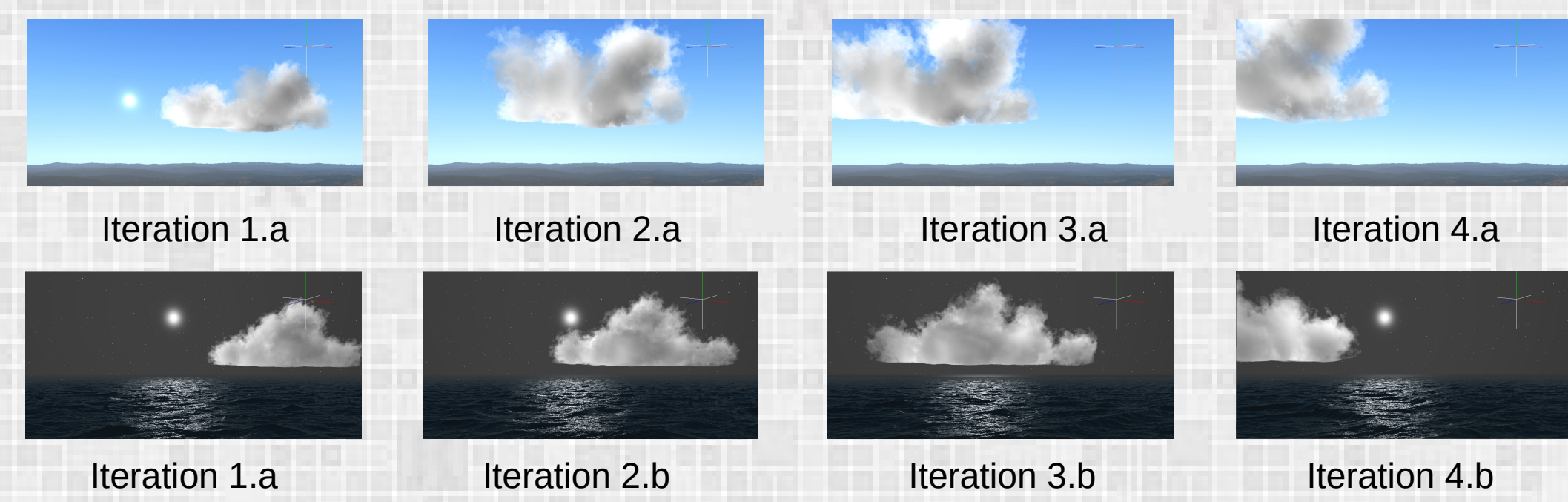
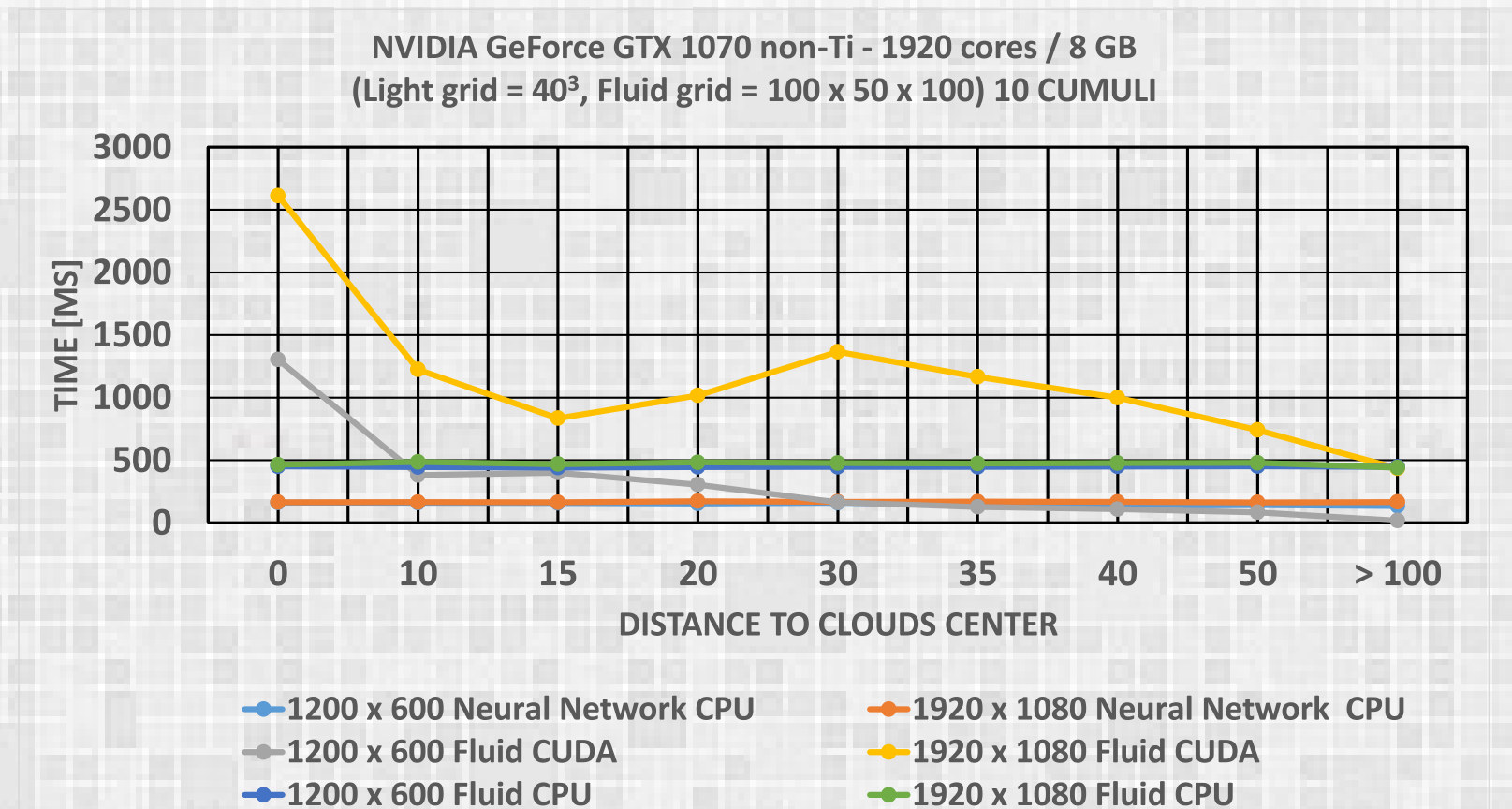


Figure 3. Four instants of a cumulus motion by using our trained RNN for fluid dynamics for 35 pseudo-spheres (a) and 60 pseudo-spheres (b) respectively.

Figure 4. Benchmark test with 35 spheres performed by using an Nvidia GeForce GTX 1070 non-Ti (Pascal, 1920 cores) running on a 64-bit i-Core 7 CPU 860@2.80 GHz (first generation, 2009) with 12 GB of RAM. Our LSTM-RNN inferences outperform the CPU and CUDA fluid algorithm counterparts.



Link to videos



Rendering quality

REFERENCES

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