PARALLEL COMPUTING ACCELERATES SEQUENTIAL DEEP NETWORKS MODEL IN TURBULENT FLOW FORECASTING

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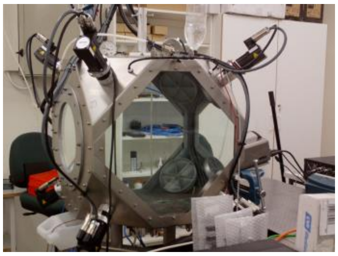
Introduction

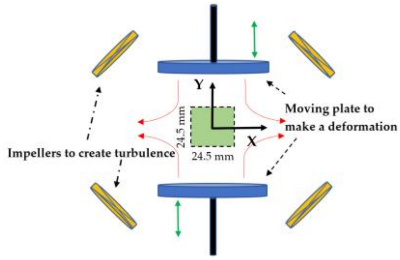
Because there is no general physical solution for turbulent flows, it is impossible to predict phenomena with this flow regime through analytical equations. Also, the study of turbulent flows is based on statistical measurements and data.

Recently, in many studies, the application of artificial intelligence in models with a sequential structure has provided the possibility of prediction in short and long term. Deep learning extracts vital features for a model and exploits them to predict the following period.



Flow facility [H. Reza, 2020]

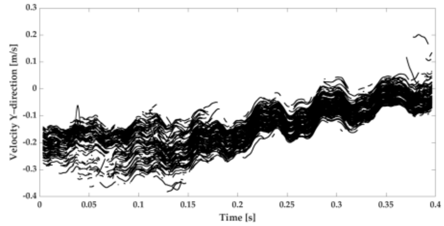
This study aims to use the statistically measured characteristics of the turbulent flow generated in the laboratory to predict the flow in the next period. Parallel computing is essential for deep learning modeling and big statistical data. The assessment of parallel computing and scalability is reported in this work.



Sketch of straining flow generating and location of the measurement area in the flow facility

Measured flow

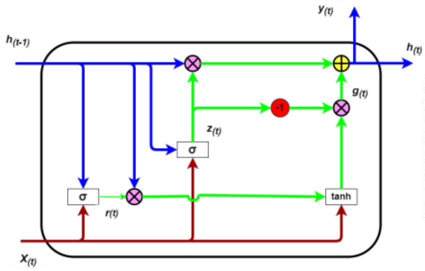
The turbulence intensity is controlled in the flow facility via impeller speed, and the strain is generated in the y direction. The flow is seeded with tracer particles with an 8-10 µm diameter and specific gravity of 1.1 g/cm3. The Lagrangian particle tracking method was employed for 2D measurement. The flow has $100<Re_{\lambda}<500$. Each particle has a specific velocity and position at a particular time. The 20-strain flows were repeated and recorded to collect appropriate statistical data. The velocity in the y direction was used to create a model and predict the following period.



Measured velocity in y direction in the generated flow

GRU model

From the Lagrangian framework, the turbulent flow has the spatial-temporal feature; we applied the gated recurrent unit model. It is the next determination of long short-term memory methods which can predict sequential dataset. The designed and used approach creates a model from measured velocity, time, and position of the fluid particle based on the Lagrangian view.



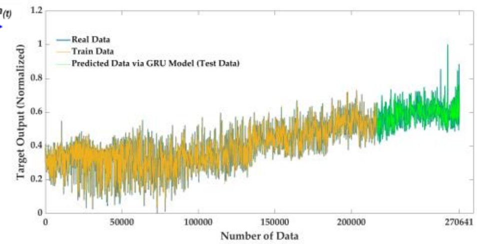
Gated Recurrent Unit (GRU) cell [H. Reza et al., 2022]

Prediction of the turbulent flow

The input dataset is composed of 272,264 particle features and has different scales; normalizing them is essential.

The data are split into 80% training and 20% test data. The GRU model is created with 100 layers. The mean absolute error and coefficient of determination are measured to assess the model.

We employed parallel computing to implement the model and make the forecasting.



Normalized velocity in y direction from the measurement

Parallel computing

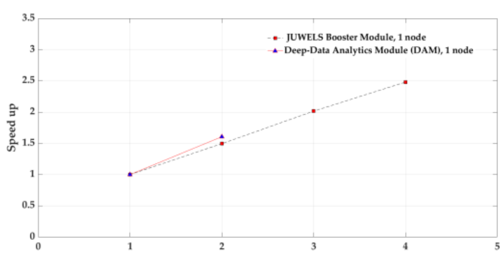
- JUWELS Booster Module:
  - 1 node involves 2× AMD EPYC Rome 7402 CPU, 2× 24 cores, 2.8 GHz
  - 936 compute nodes
  - 3,744 GPUs
- DEEP-EST, Data Analytics Module (DAM):
  - 1 rack with 16 nodes, Nodes
  - 2 x Intel (R) Xeon (R) CPU, 384 GB DDR4, 2 TB non-volatile DIMM (NVM), 1 Nvidia (R) V100 (R) 32GB HBM2 GPU 1 Intel (R) Stratix 10 FPGA 32GB DDR4
  - Processors: 32 x Intel (R) Xeon (R) Platinum 8260M Scalable Processor @ 2.4GHz (768 cores total)

Scalability

Two powerful parallel computing machines were employed to assess the scale computing to implement the GRU model training. JUWELS booster module assessed with 1 to 4 GPUs with one node. The DEEP-EST machine scale was also evaluated on 1 node with 1 and 2 GPUs.

Parallel computing machine scalability to create the GRU model with GPUs

Parallel Machine/Module	Nodes	GPUs	Computing time [s]	Speed-up
JUWELS/ Booster Module	1	1	940.643	1.000
	1	2	629.094	1.495
	1	3	466.445	2.016
	1	4	379.135	2.481
DEEP-EST/ DAM Module	1	1	881.813	1.000
	1	2	548.754	1.606



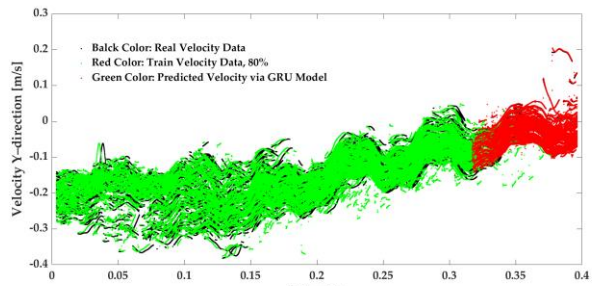
Computing scalability: JUWELS BOOSTER MODULE and DEEP-EST DAM MODULE

Model assessment

The result of the designed model presents MAE=0.002 and R2=0.98. The assessment mentions a considerable outcome from this approach and could be developed for similar applications.

MAE and *R2* evaluation for the GRU model

Training Data Model	*Mean Absolute Error (MAE)*	*R^2 Score*
80%	0.002	0.980
70%	0.002	0.984
60%	0.003	0.987



GRU model for turbulence flow velocity in y direction forecasts the next time step and assessed with actual data

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