The Capability of Recurrent Neural Networks to Predict Turbulence Flow via Spatiotemporal Features

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***Abstract*—This study presents a deep learning (DL) neural network hybrid data-driven method that is able to predict turbulence flow velocity field. Recently many studies have reported the application of recurrent neural network (RNN) methods, particularly the Long short-term memory (LSTM) for sequential data. The airflow around the objects and wind speed are the most presented with different hybrid architecture. In some of them, the data series is used with the known equation, and the data is firstly generated. Data series extracted from Computational Fluid Dynamics (CFD) have been used in many cases. This work aimed to determine a method with raw data that could be measured with devices in the airflow, wind tunnel, water flow in the river, wind speed and industry application to process in the DL model and predict the next time steps. This method suggests spatial-temporal data in time series, which matches the Lagrangian framework in fluid dynamics. Gated Recurrent Unit (GRU), the next generation of LSTM, has been employed to create a DL model and forecasting. Time series data source is from turbulence flow has been generated in a laboratory and extracted via 2D Lagrangian Particle Tracking (LPT). This data has been used for the training model and to validate the prediction in the suggested approach. The achievement via this method dictates a significant result and could be developed.**

***Index Terms*—Recurrent Neural Network, Unsteady Flow, Deep Learning**

I. Introduction

Turbulence is observed in the most natural and artificial phenomena [1] [2]. Water in the waterfall, airflow in the wind, smoke from a chimney, and airflow around the objects are examples from the environment [1]. The industry cases are the flow in the engine mixing chamber; two working flows inside the heat exchanger, and airflow around the airplane and car [1] [3] [4] [5]. In large-scale turbulence, solar flare, oceanic and atmospheric flow are other giant emanations that influence our lives [2]. The turbulence flow almost everywhere [1]. Turbulence flow is chaotic, nonrepeatable, and random, and it is well addressed that the statistics aspect of the flow is applicable [1]. On the other hand, Computational Fluid Dynamics (CFD) is a leading traditional numerical approach to dealing with nonlinear fluid dynamics phenomena such as turbulence flow. Direct Numerical Method (DNS) and Large Eddy Simulation (LES) are two capable and accurate methods to resolve the turbulent flow problems. But, from the computational cost, they are costly. High-performance computation (HPC) is an essential factor for all solutions in DNS and LES. Simulation for many types of turbulence problems is almost impossible on the actual scale because of the limitation in the computation. Scientists have efforts to create similar scale problems to natural phenomena. However, we are still far from solving problems with extensive size. In many CFD applications, it is required to validate the solution with empirical data, is an another limitation. These constraints illustrate a reliable tool is necessary to overcome the above-called obstacles. Machine learning (ML) based on Artificial Intelligence (AI) has become an important key to encountering nonlinear phenomena. Deep learning (DL) is a capable approach in ML and is able to extract the hidden features from complex and nonlinear dynamic systems [6] [7]. Recurrent neural network (RNN) is a type of neural network especially appropriate for sequential data such as time series [6]. An RNN is a neural network composed of an individual hidden layer with a feedback loop in which the hidden layer output with the current input is returned to the hidden layer [6]. RNN network defines the temporal relationship because of sequential input data, and three weight matrices and two biases characterize it. RNNs can almost not train sequence data with long-range temporal dependencies because the vanishing gradients problem exists [6]. Long short-term memory (LSTM) network was developed and suggested in 1995 [8]. LSTM applies a gating structure to control the transients of the recurrent connectors and can deal with the vanishing gradient issue. Moreover, it is able to model longer temporal dependencies rather than standard RNNs [6]. Recently, LSTM has been employed in many studies in order to model time series prediction. The interest in this method has

This work was performed in the Center of Excellence (CoE) Research on AI and Simulation Based Engineering at Exascale (RAISE) and the EuroCC projects receiving funding from EU's Horizon 2020 Research and Innovation Framework Programme under the grant agreement no.951733 and no. 951740 respectively.

also increased in the fluid dynamics area. Vinuesa et al. [6] have used LSTM to predict the turbulence shear flow. Veisi et al. [7] used LSTM hybrid model prediction for unsteady flows. LSTM Potential has been led to hybrid models such as convolutional neural network (CNN)–LSTM, Autoencoders–LSTM, and LSTM/RNN [9]. Gated recurrent unit (GRU) [10] is a variant of LSTM which has fewer parameters than LSTM, and the training rate is faster [9]. In GRU, the forget gate and input gate in LSTM are replaced with only one update gate [9]. GRU is required fewer data to train the model, therefore gaining a similar performance in multiple tasks with less computation [9]. Recently GRU has been employed to forecast wind speed and predicts electricity demand [10] [11] [12]. Most fluid flow studies that were applied ML/DL are composed of data extracted from CFD studies' known equations. On the other hand, many works included preliminary steps to do autoencoder to extract the main features, such as, proper orthogonal decomposition (POD), dynamic mode decomposition (DMD), and well-known reduced order methods (ROMs) [7] [13] [14] [15]. In the ML/DL context, there is a capability to determine a training method with raw data from the Lagrangian framework velocity field involving spatial and temporal features. In many applications of industry, research and experiment, it is possible to measure the velocity field directly or indirectly via devices such as constant temperature anemometer (CTA), flowmeter (and obtain the velocity), pitot tube, laser doppler anemometry (LDA), and light detection and ranging (LIDAR). This study introduces a method to use time series data consisting of velocity components and position in 2D coordinate to train the GRU model and evaluate the prediction in future time. Hence, this paper is organized as follows. The applied theory is presented in Section II. In Section III, the method is introduced. Section IV discusses the result, and the conclusions are presented in Section V.

II. Theory

A. Lagrangian Framework in fluid dynamics

Lagrangian framework is a description of the motion fluid, involves keeping track of the position vector and velocity vector of each point of flow which it is called fluid particle [1] [16]. A fluid particle is a point that moves with the local fluid velocity, therefor it specifies the position at time t of fluid particle [16]. The definition of fluid particle mathematically is [1]:

$$x_i = x_i(t, x_{i,0}) \quad , \quad i = 1, 2, 3 \tag{1}$$

$$U_i = U_i(t, x_1(t, x_{1,0}), x_2(t, x_{2,0}), x_3(t, x_{3,0})) \quad , \quad i = 1, 2, 3 \tag{2}$$

Where (1) and (2) determines the fluid particle position and velocity in 3D coordinates respectively. x is the position, U is the velocity, t is the time and denote i specifies the vector component. Based on the Lagrangian definition, for fluid particle there is a time series data which specify a position and velocity at particular time. Particularly in turbulence flow which has not known equation and it is investigated in statistics, these time series data available and appropriate to use.

B. Gated Recurrent Unit (GRU)

From the DL method, it is well known that RNNs can perform prediction for sequence data via Long Short Time Memory (LSTM). Gated Recurrent Unit (GRU) [17] is a next-generation defemination from LSTM with a bit distinction in the model architecture. Literature reports that GRU is comparable in performance is considerably faster to compute than LSTM and has a streamlined model [18]. GRU cell that is displayed in Fig. 1, is composed of a hidden state, reset gate, and update gate. We can control how much of the previously hidden state might be remembered from the reset gate. On the other hand, via the update gate, we can understand how much of the new hidden state is just a copy of the old hidden state. This architecture in the GRU establishes two significant features: the reset gate captures short-term dependencies in sequences, and the update gate receives long-term dependencies in sequences [17].

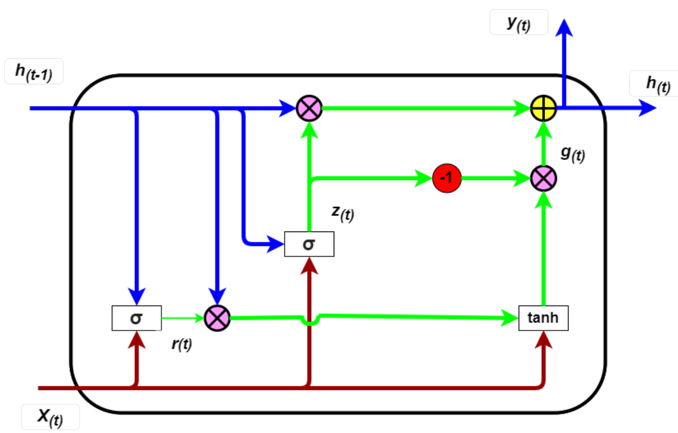

Fig. 1. Gated Recurrent Unit (GRU) cell

III. Methodology

A. Velocity time series data

This study has designed and applied a suggested hybrid model based on time series vector data for velocity. The spatial and temporal data extracted from 2D Lagrangian Particle Tracking (LPT) have been recorded in the laboratory. The flow is turbulence with straining deformation generated in the experiment. Data is included time, velocity in x and y directions, and position in x and y coordinates. Therefore, we have corresponding velocity and position with a specific time in this time series. In the suggested model, since the velocity is with two components in the x and y direction, we carried on the model for every component individually. Hence, the model predicts the velocity component in both directions and then could be developed in 3D time-series data. The used data in this work, have been recorded during an empirical straining turbulence deformation in 0.4 s.

B. GRU model

The proposed GPU model is created with data series involving two velocity components in x and y directions and two-position coordinates x and y. Every fluid particle at a specified time has a velocity component, and based on the Lagrangian view; they are dependent on the time and position. Both position vectors also function of time and primary position. The input features are on different scales, and then it is essential to scale the features. A function is defined to create time-series data set. The data are split into 80% training and 20% test data set. The GRU model is created with one GRU layer and one Dense layer, and the model is optimized with an Adam optimizer. In order to evaluate the model, the mean absolute error (MAE) and coefficient of determination (R^2) are measured.

IV. Result

The explained method in the study is based on the capability of DL via GRU, which is able to store long-term dependencies. Fig. 2 represents the result of this model that has been used to predict the velocity components in the y-direction. In Fig. Fig. 2, the actual data, hidden and covered by train data and predicted data, dictates the suggested model could make remarkable forecasting for a future time.

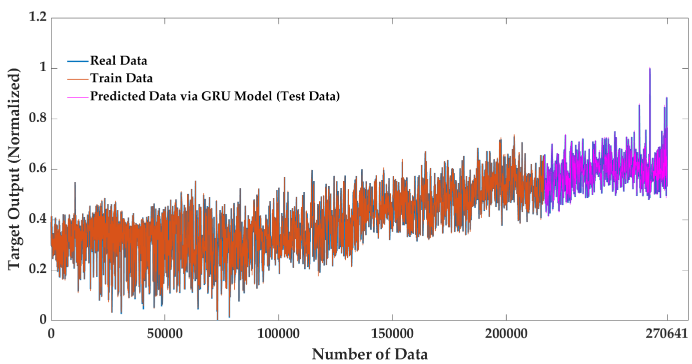

Fig. 2. GRU model for turbulence flow velocity in y direction with spatial temporal features

For the conducted model, MAE and R^2 were measured equal to 0.002 and 0.98, respectively. These measurements determine that the GRU model can establish a significant prediction for time series with features that have relationships analogous to described data in this work that could be seen in many turbulence flow applications.

V. Conclusion

This work aimed to determine a method to use spatial-temporal features of the Lagrangian framework data in a turbulent flow to create a prediction model based on DL authority. In this view, the velocity functions of the position and time. On the other hand, the position is related to the time and primary place. DL networks for sequential data have been developed in subsets in RNNs such as LSTM and GRU. Turbulence flow is a high dimensional phenomenon, and to use a feature for LSTM/GRU model, it is essential to figure out the main features among the high-dimensional data. This study proposed a GRU model relying on velocity components and the position of the fluid particles and exclusive of high dimensionality. Moreover, GRU can predict a time series with long-term dependencies based on the result presented and the Lagrangian definition for the velocity field, storing long-term dependencies is a crucial factor that led to this significant prediction and matched the actual data in the test. On the other hand, this method creates predictions for every velocity component individually, making it applicable for 2D and 3D fluid flow. The error measurement represented in the evaluation of this method implies the capability of GRU in this kind of application and could be developed for long-term forecasting studies.

Acknowledgment

We thank Prof. Ármann Gylfason from Reykjavik University for his technical comments on the experiment conducted at the Laboratory of Fundamental Turbulence Research (LFTR) at Reykjavik University. We also acknowledge Prof. Chung-Min Lee from California State University Long Beach for her assistance.

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