CENTER FOR CONNECTED AND AUTOMATED TRANSPORTATION

Final Report #ICT-21-036
November 2021

Data-Driven Computation Fluid Dynamics Model for Predicting Drag Forces of Truck Platoons

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DISCLAIMER

Funding for this research was provided by the Center for Connected and Automated Transportation under Grant No. 69A3551747105 of the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program. The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Suggested APA Format Citation:

Meidani, H., & Kazemi, A. (2021). *Data-driven computational fluid dynamics model for predicting drag forces on truck platoons* (Report No. ICT-21-036). Illinois Center for Transportation. https://doi.org/10.36501/0197-9191/21-036

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
ICT-21-036	N/A	N/A

4. Title and Subtitle	5. Report Date
Data-Driven Computational Fluid Dynamics Model for Predicting Drag Forces on Truck Platoons	November 2021
	6. Performing Organization Code N/A
7. Authors Hadi Meidani, Amir Kazemi	**8. Performing Organization Report No.** ICT-21-036 UILU-ENG-2021-2036
9. Performing Organization Name and Address Illinois Center for Transportation, Department of Civil and Environmental Engineering, University of Illinois at Urbana–Champaign, 205 North Mathews Avenue, MC-250, Urbana, IL 61801	**10. Work Unit No.** N/A **11. Contract or Grant No.** Grant No. 69A3551747105
12. Sponsoring Agency Name and Address Center for Connected and Automated Transportation, University of Michigan Transportation Research Institute, 2901 Baxter Road, Ann Arbor, MI 48152	**13. Type of Report and Period Covered** Final Report **14. Sponsoring Agency Code** Center for Connected and Automated Transportation

15. Supplementary Notes

Funding under Grant No. 69A3551747105 U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology (OST-R), University Transportation Centers Program.
https://doi.org/10.36501/0197-9191/21-036

16. Abstract

Fuel-consumption reduction in the truck industry is significantly beneficial to both energy economy and the environment. Although estimation of drag forces is required to quantify fuel consumption of trucks, computational fluid dynamics (CFD) to meet this need is expensive. Data-driven surrogate models are developed to mitigate this concern and are promising for capturing the dynamics of large systems such as truck platoons. In this work, we aim to develop a surrogate-based fluid dynamics model that can be used to optimize the configuration of trucks in a robust way, considering various uncertainties such as random truck geometries, variable truck speed, random wind direction, and wind magnitude. Once trained, such a surrogate-based model can be readily employed for platoon-routing problems or the study of pavement performance.

17. Key Words	18. Distribution Statement
Truck Platooning, Drag Forces, Fuel Consumption, Data-Driven Models, Deep Neural Networks	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	17	N/A

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

ACKNOWLEDGMENT, DISCLAIMER, MANUFACTURERS' NAMES

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CHAPTER 1: INTRODUCTION

OVERVIEW

The trucking industry in 2019 contributed to 72.5% (11.84 billion tons) and 80.4% ($791.7 billion) of the nation's freight weight and revenue, respectively. More than 40 million trucks traveled a mileage of about 490 billion miles in 2018 (American Trucking Association, 2020). Commercial and freight trucks comprised 24.1% of the total US transportation energy use in 2019, while transportation's share of the total US energy consumption was 28% (US Energy Information Administration, 2021). Besides, heavy-duty vehicles are responsible for 20% of greenhouse gas emissions by the transportation sector in the United States (Quiros et al., 2017). Therefore, fuel-consumption reduction in the trucking industry is significantly beneficial to both energy economy and the environment.

Intelligent transportation systems (ITS) and the development of autonomous vehicles are enabling truck platooning as a promising solution to fuel efficiency in the trucking industry. A truck platoon, or convoy, is a train of trucks that travel with small spacings between them to benefit from reduced air resistance (drag force). The study of drag-force reduction in truck platoons requires either experimental wind tunnel tests or computational fluid dynamics, CFD (Bhoopalam et al., 2018; Tsugawa et al., 2016; Zhang et al., 2020). CFD computations are computationally expensive, especially when the number of bodies in the fluid increases and when uncertain factors are considered, as is the case in our truck-platooning problem. We aim to develop a surrogate-based fluid dynamics model that can be used to optimize the configuration of trucks in a robust way, considering various uncertainties such as random truck geometries, variable truck speed, random wind direction, and wind magnitude. Once trained, such a surrogate-based model can be readily employed for platoon-routing problems or the study of pavement performance.

OBJECTIVES

A surrogate-based fluid dynamics model for truck platoons is trained by a training dataset obtained from runs of a CFD simulation.

In this work, we seek to create a model that accounts for variability and/or uncertainty in

- the number of trucks in the platoon
- truck geometry and the position of trucks with respect to each other (lateral positioning and headway)
- the traveling speed of the platoon and the wind magnitude and direction

all of which affect the drag force applied on the trucks.

We have investigated supervised training of a deep neural network (DNN) as an effective prediction model of the drag forces for a given set of variables mentioned above.

CHAPTER 2: BACKGROUND ON CFD AND DATA-DRIVEN MODELS

In this chapter, we provide background on the governing equations in computational fluid dynamics and the related literature on using fast surrogates to replace time-consuming CFD simulations. We also summarize the literature on modeling uncertainties related to wind magnitude and direction. Finally, a short background on deep neural networks, which is the mathematical form of our surrogate, is included.

CFD GOVERNING EQUATIONS

The motion of viscous fluid is governed by the Navier-Stokes equation, which can be written in different forms; see Figure (1)

$$\text{Convective Form:} \qquad \rho \frac{\mathrm{D}\mathbf{u}}{\mathrm{D}t} = -\nabla p + \nabla \cdot \boldsymbol{\tau} + \rho \mathbf{g}$$

$$\text{Conservation Form:} \qquad \frac{\partial}{\partial t}(\rho \mathbf{u}) + \nabla \cdot (\rho \mathbf{u} \otimes \mathbf{u}) = -\nabla p + \nabla \cdot \boldsymbol{\tau} + \rho \mathbf{g}$$

Figure 1. Navier-Stokes equation.

where D/Dt is the material derivative, defined as $\partial/\partial t + u \cdot \nabla$, ρ is the density, u is the flow velocity, $\nabla\cdot$ is the divergence, p is the pressure, t is time, τ is the deviatoric stress tensor, and g represents body accelerations acting on the continuum.

The behavior of fluid, however, is typically chaotic; and the numerical solution of Navier-Stokes may not converge. To avoid this problem, Reynolds-Averaged Navier-Stokes (RANS) are used, along with turbulence models such as the k-epsilon model that is used in this work.

MOTIVATION BEHIND DATA-DRIVEN MODELS

Solving computational fluid dynamics problems is usually expensive for practical systems. Even though such a computational burden makes CFD results precious for potential further usage, obtained simulation data are disposed of once projects are over. The discard of CFD simulation results is done mainly because they are deemed to be project-specific data lacking a prospect for further applications and is also motivated by avoiding their storage cost, especially for large 3D transient-analysis cases. The development of machine-learning methods in the past decade has triggered a new wave of studies for exploiting CFD results to train surrogate models. In this chapter, three recent applications of CFD data-driven models are reviewed to highlight the significance of the approach.

RECENT WORKS ON CFD DATA-DRIVEN SURROGATE MODELS

Wind Load of Buildings (Sang et al., 2021)

Wind-load calculation is critical for structural design, especially for tall buildings where vibration is of additional importance. Using neural networks for predicting wind loads for different cross sections of buildings helps to avoid computationally expensive CFD for future designs. For different aspect ratios of a rectangular cross section, as well as different velocities and angles of attacks, drag coefficients are obtained from CFD. The generated data is then used in a supervised learning to train a deep neural network model that can predict drag coefficient for a given cross section, velocity, and angle of attack. The results of predictions using the trained model agree with the ground truth from CFD; see Figures (2-4).

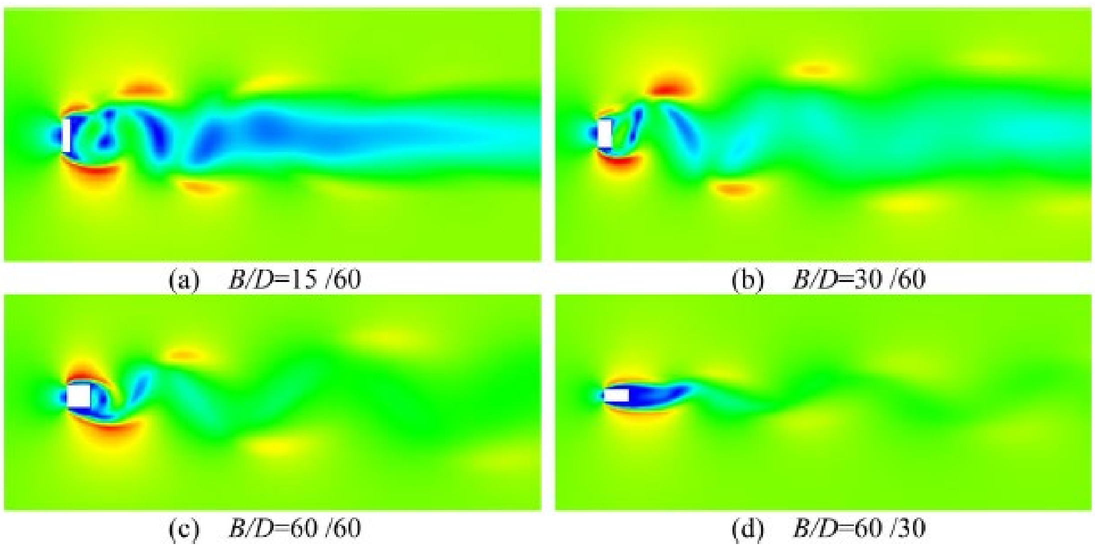


Figure 2. Velocity field for different aspect ratios of a building cross section (Sang et al., 2021).

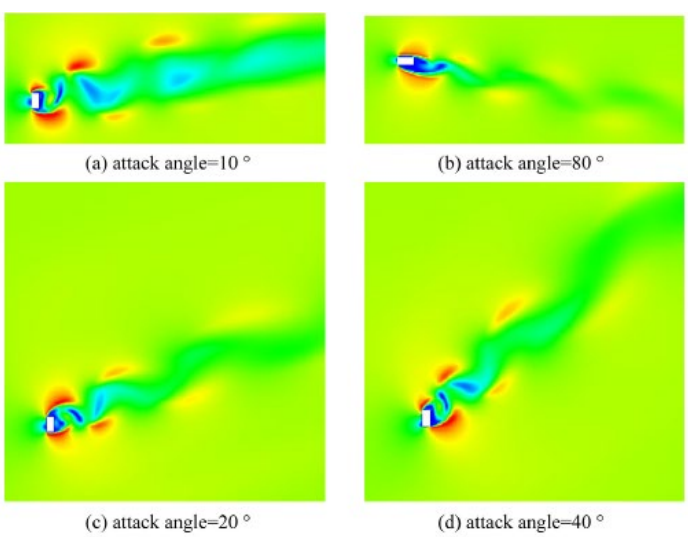


Figure 3. Velocity field for different angles of attack (Sang et al., 2021).

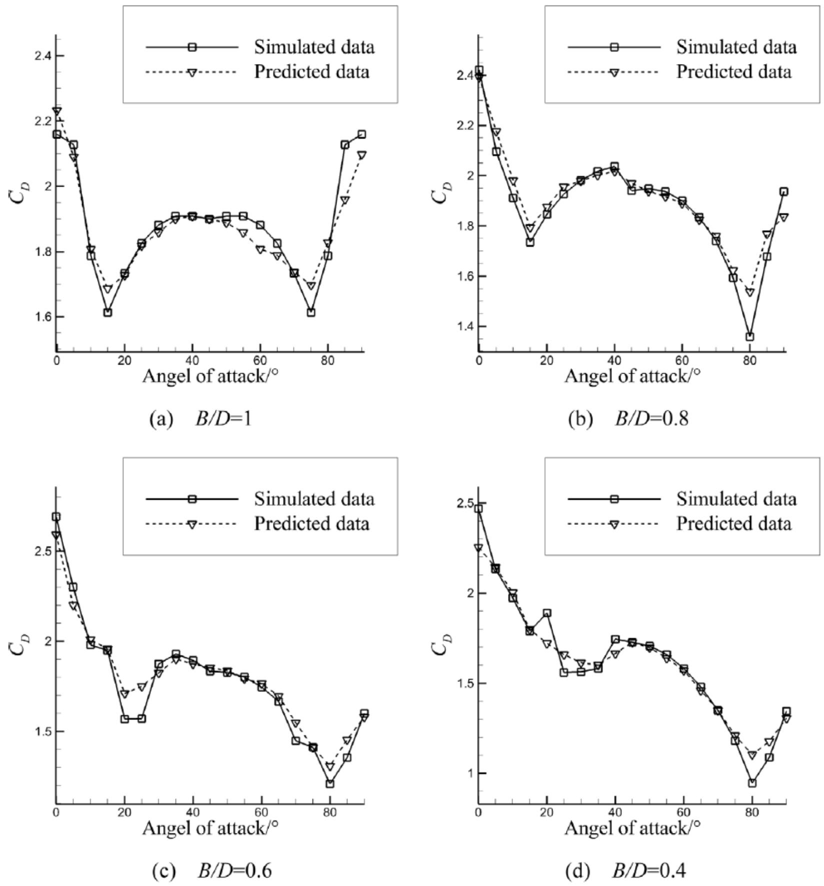


Figure 4. Drag coefficient verification results for different aspect ratios and angles of attack (Sang et al., 2021).

Multiphase Flows (Ganti and Khare, 2020)

Data from direct numerical simulations of multiphase-flow processes are employed to train a spatiotemporal surrogate model using Gaussian-based machine learning. Simulations are performed assuming the incompressible Navier-Stokes equations. The framework of surrogate modeling includes four steps:

1. *Data generation:* Based on a ground-truth model, a design of experiment (DoE) is carried out to obtain enough data points in space and time. These data are then used to train the model, which predicts (or emulates) the results.

2. *Dimensionality reduction:* The dimensionality of training data is reduced using principal-component analysis, which produces eigenmodes, spatial basisfunction, and temporal coefficients.

3. *Regression:* The results from dimensionality reduction in the previous step are treated as inputs to Gaussian process regression. The trained model is expected to emulate the dynamics of the system for any given operating conditions.

4. *Evaluation:* Flow fields are reconstructed using Galerkin estimation, which is then used for error quantification.

The steps of modeling are presented in Figure 5.

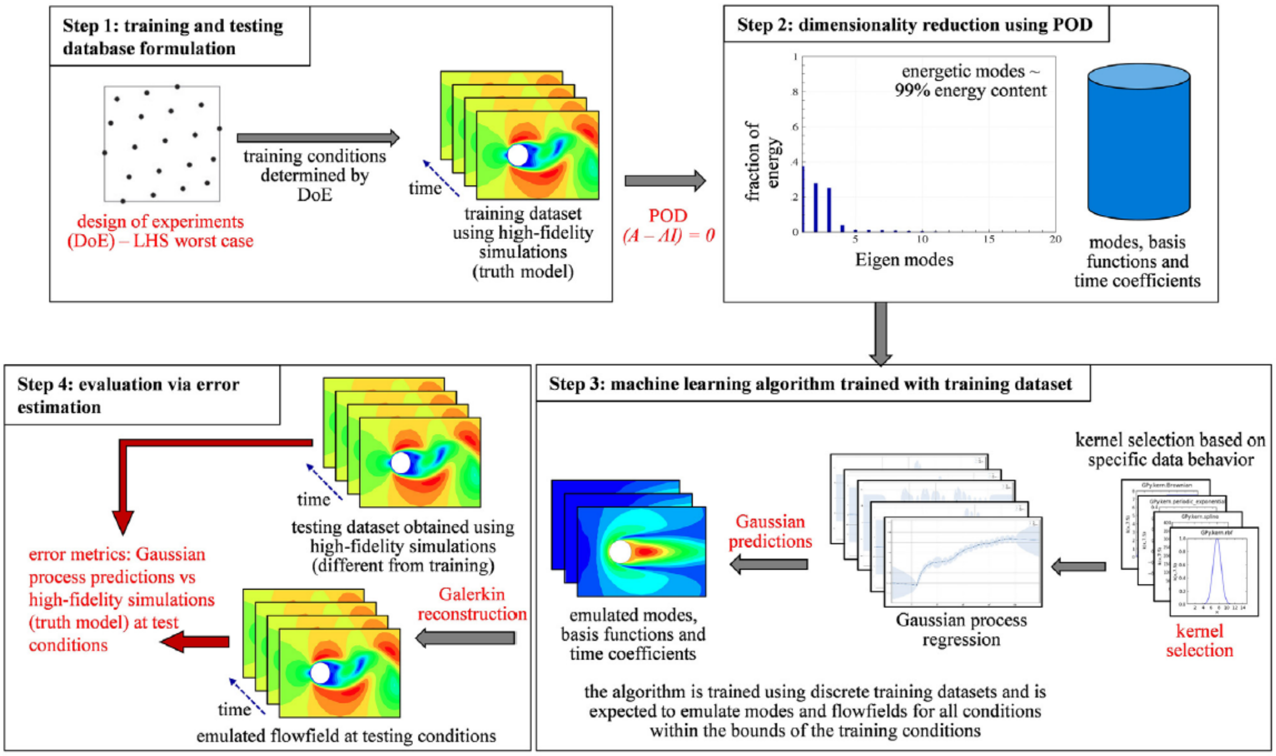


Figure 5. Surrogate CFD modeling for porous-media flows (Ganti and Khare, 2020).

The proposed framework is examined for two examples: (1) flow over a cylinder and (2) injection of diesel jet into a quiescent nitrogen chamber. As presented in the following figures, the emulation results are very similar to the ground truth; see Figure 6

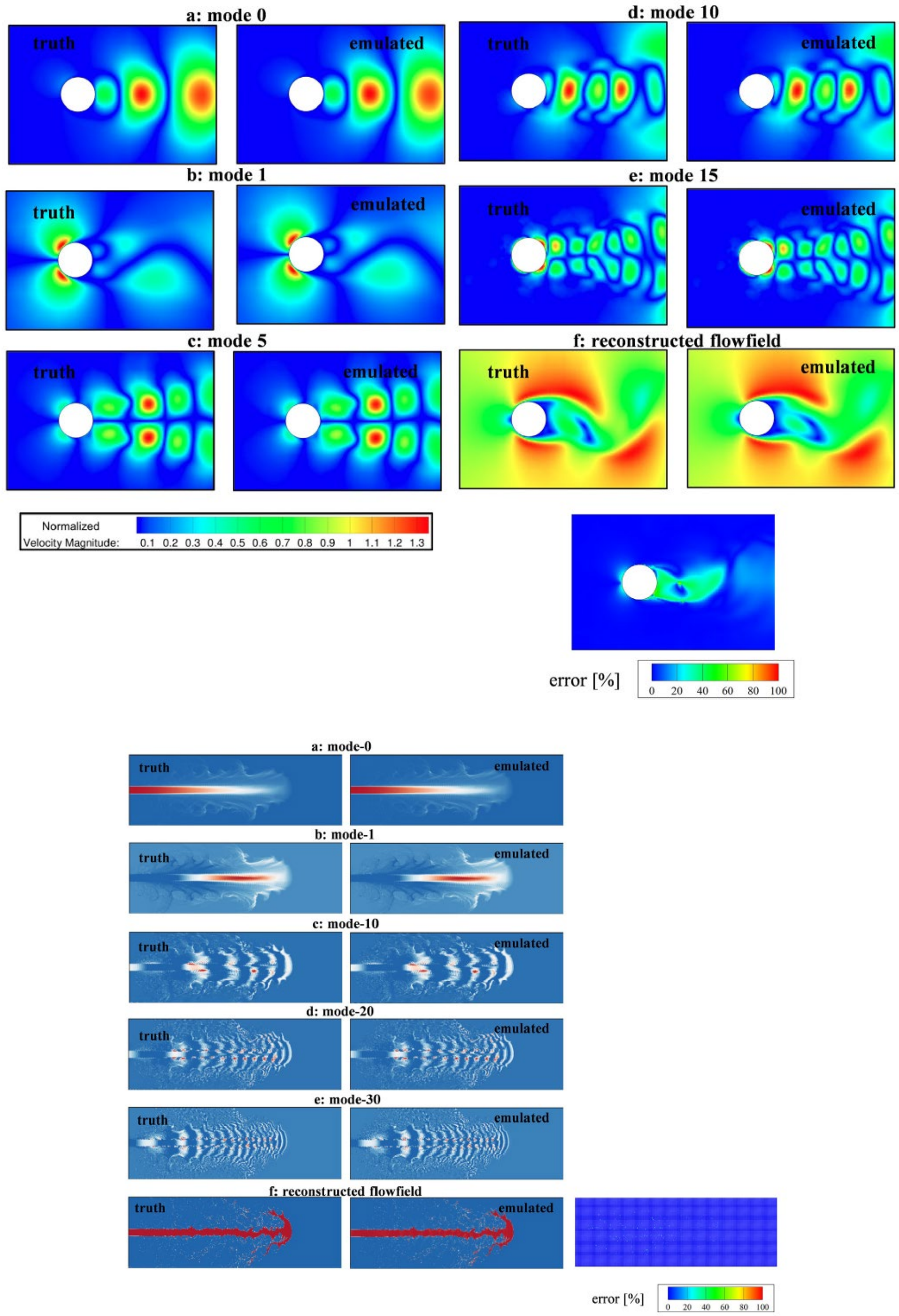


Figure 6. Surrogate CFD modeling for multiphase flows: emulation vs truth simulation (Ganti and Khare, 2020).

Porous-Media Flows (Takbiri-Boroujeni et al., 2020)

Numerical flow-simulation data in porous media are used to train a surrogate model for predicting velocity fields and permeability tensors. The prediction may be applied to porous media that have not been used in the training. Surrogate-model results demonstrate a high accuracy relative to lattice Boltzmann simulation (Figure 7). Capturing the physics of the problem, such surrogate models reduce computational costs with respect to both memory and speed for the same numerical resolution.

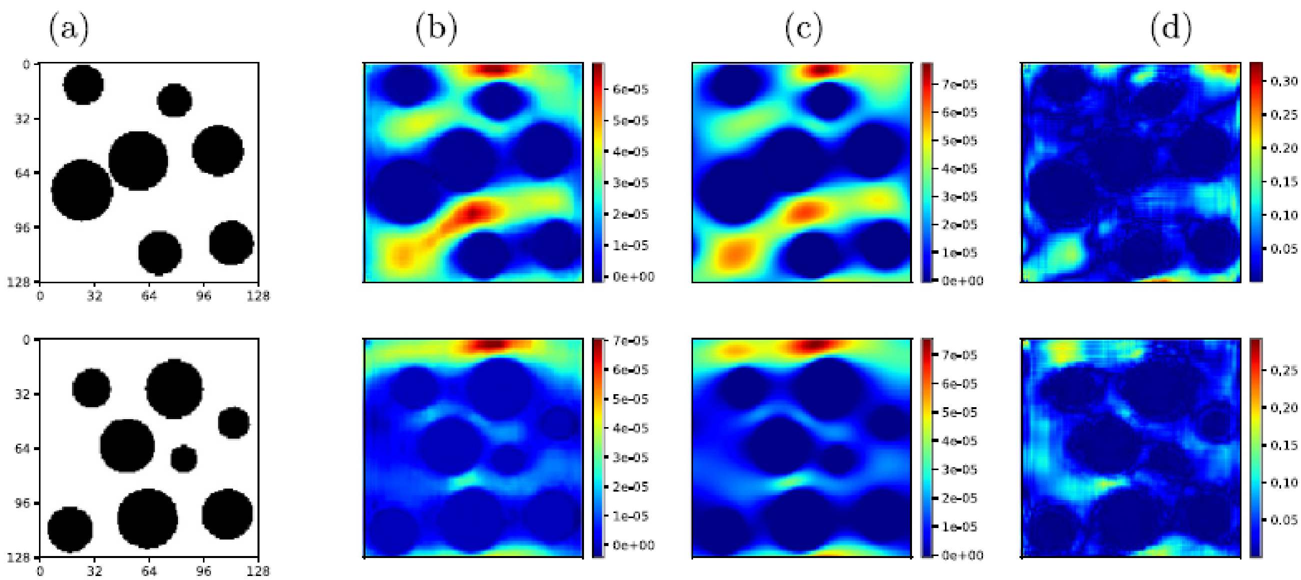


Figure 7. Surrogate modeling for porous media flows: (a) random porous media, (b) velocity from data-driven model, (c) velocity from truth simulation, and (d) error (Takbiri-Boroujeni et al., 2020).

A NOTE ON WIND UNCERTAINTY (HE ET AL., 2010)

The magnitude and direction of wind affect the aerodynamics load applied to traveling vehicles. These wind parameters are uncertain during the movement of vehicles. The drag force and the fuel consumption of truck platoons are affected by wind uncertainty, which can be quantified for different geographical areas. The Weibull distribution is usually used for land-surface wind speeds (SWS). For North America, the parameter of Weibull distribution has been obtained for 3-hourly records for 720 stations from 1979 to 1999. The distribution parameters depend on daytime/nighttime, land types, and seasons. At night, the Weibull distribution substantially underestimates the skewness of SWS over mountains, forests, and open land for larger values of the mean speed. For daytime, however, the Weibull curve is a well-fit model for SWS over all surface types and for every season (see Figure 8).

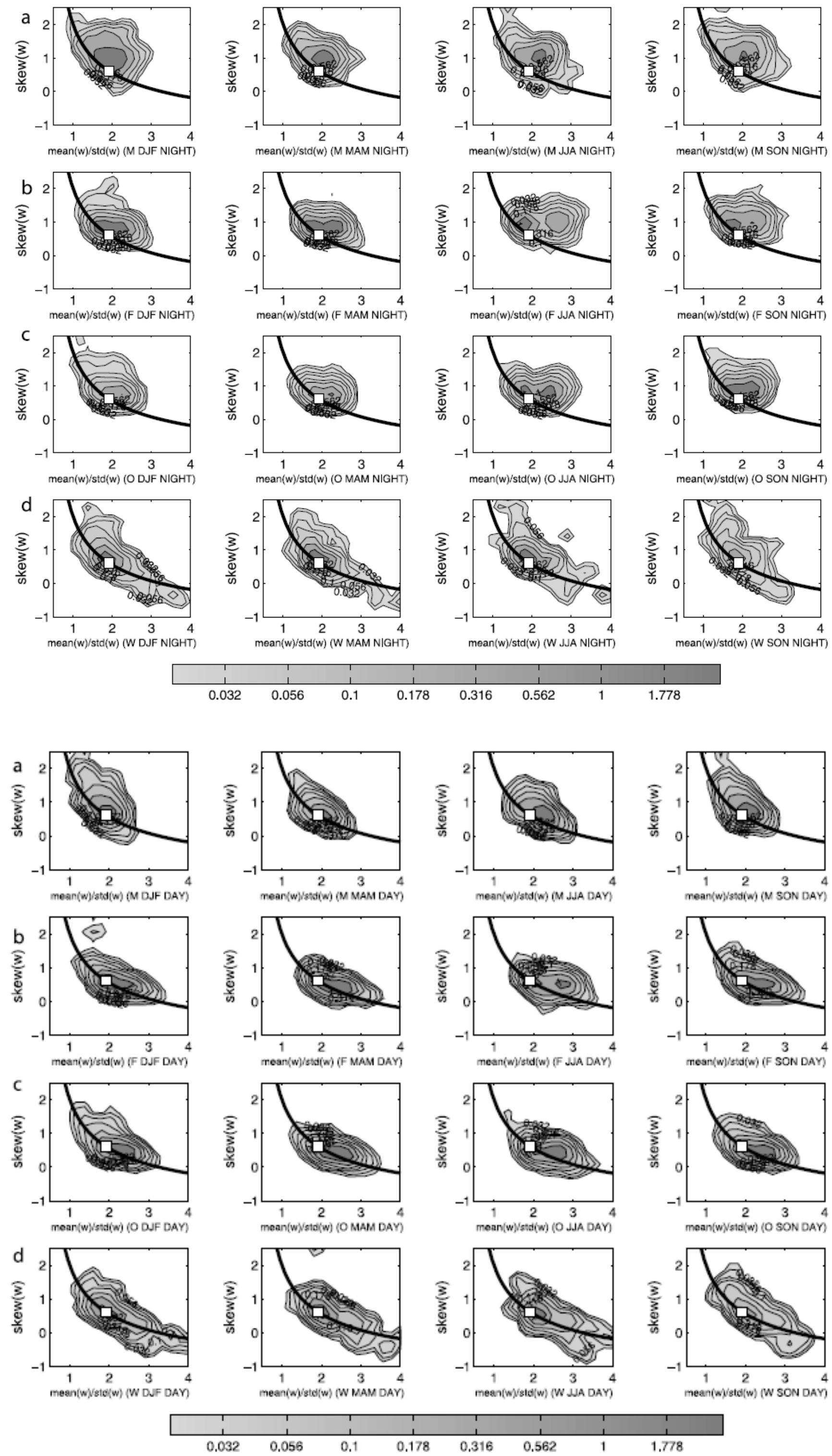


Figure 8. The skew and mean values of Weibull distribution for different land types: mountain (M), forest (F), open land (O), and open water (W); and different seasons: December–February or DJF; March–May or MAM; June–August or JJA; and September–November or SON (He et al., 2010).

A NOTE ON DEEP NEURAL NETWORKS

A deep neural network (DNN) is a model, inspired by the neurons in the brain, to approximate nonlinear functions. It consists of three types of layers: input, hidden, and output. Consider the following DNN that has two inputs, a single hidden layer with five neurons, and one output. Neurons' connections are associated with weights (W) and biases (b), which through an activation function (Φ) give the output at each neuron. The model parameters (W) are optimized to minimize a loss function (J(W)), which is a distance between the output and the target values ,see Figure 9

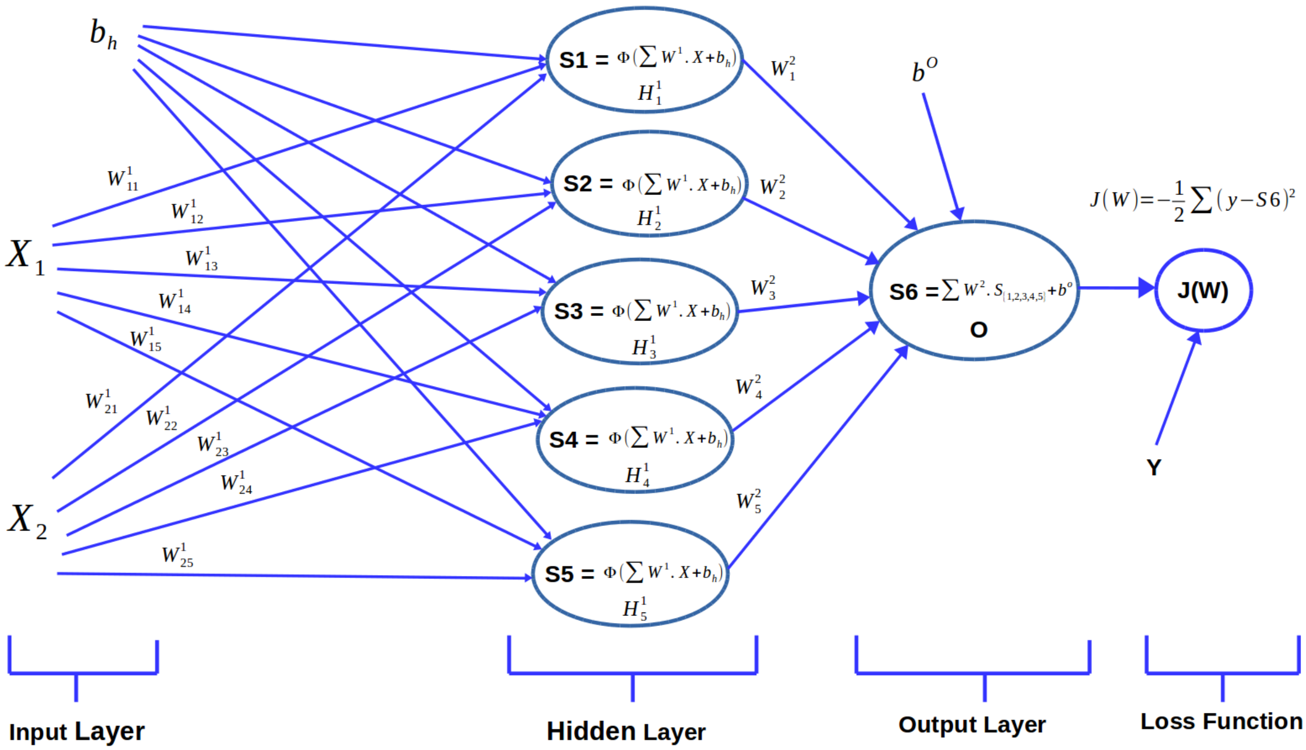


Figure 9. A single hidden-layer neural network (Chouksey, 2020).

Optimization of the model is usually performed by the stochastic gradient method (SGD) where the true gradient of *J(W)* is approximated at a single sample (or a mini-batch of samples) and is formulated as $W \coloneqq W - \eta \nabla J_i(W)$ with $J_i(W)$ denoting the single sample (or mini-batch) loss value and η as the learning rate (or step size). Training by SGD is performed by shuffling samples multiple times until convergence occurs.

CHAPTER 3: SIMULATION

SIMULATION ENVIRONMENT

Training a surrogate-based fluid dynamics model that addresses the variability and/or uncertainty of inputs requires a parametric analysis tool. ANSYS Fluent has the ability to parametrize the system input and outputs, which is called design of experiment (DoE). Also, surrogate-based fluid dynamics models require a large sample of CFD results, which can be obtained only through high-performance computing (HPC). Integration of ANSYS Fluent DoE and HPC provides a tool for generating CFD data efficiently. All the CFD simulations will be in parallel, executed on National Center for Supercomputing and Application (NCSA) iForge clusters, which hosts ANSYS. The iForge cluster has 44 Skylake nodes, with each node including 40 Intel Skylake cores. There are also 2 GPU nodes available, each including 40 Intel Skylake cores and 4 V100 GPUs. The hardware has been well benchmarked to efficiently run CFD simulations and train a large-scale deep-learning model in parallel.

CASE STUDIES

CASE 1: Two-Truck Platoon

A parametric two-truck platoon is designed as a proof of concept to demonstrate the data-driven model learnability. The model predicts the total drag force of the system for a given truck geometry, headway, lateral offset, velocity inlet magnitude, and direction. The parametric model is presented in Figure 10 and Figure 11. The velocity results of the transient CFD analysis are illustrated in Figure 12, which shows how a lateral positioning of the trucks affects the velocity field and, consequently, the drag force. Based on the results for 968 realizations of the system, a dense deep neural network (Figure 13) was trained by 85% of the dataset to predict the overall drag force of trucks from 15 input parameters (geometry and speed). As presented in Figure 14, with a dataset of under 1,000, the accuracy of the model is around 90%.

noseL = unif(0,2)
cabL = unif(2,3)
trailerL = unif(6,18)
wdL = unif(0,cabL)
wdH1 = unif(0,1)
wdH2 = unif(1,1.5)
cabH = unif(2.5,3.5)
trailerH = wdH2 + cabH
noseH1 = unif(1.5,2)
noseH2 = noseH1 + (noseH1<1.75)*unif(0,0.5)+(noseH1>=1.75)*unif(0,0.25)
truckW = unif(2.4,2.6)/2
velmag = unif(11.2,31.3) # 25 to 70 mile/hr
veldirX = 1
veldirY = unif(-0.3,0.3)
veldirZ = unif(-0.3,0)
HeadwayT2 = (noseL+cabL+trailerL)*(1+unif(0.1,0.2))
LatT2 = unif(0,1)

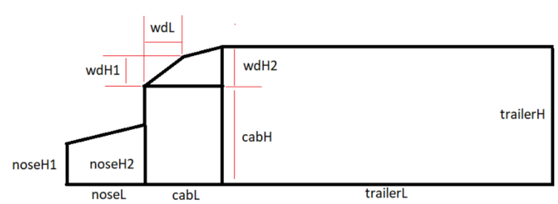


Figure 10. Parametric model of trucks. Unif(a,b) represents uniform distribution between a and b. Units are SI.

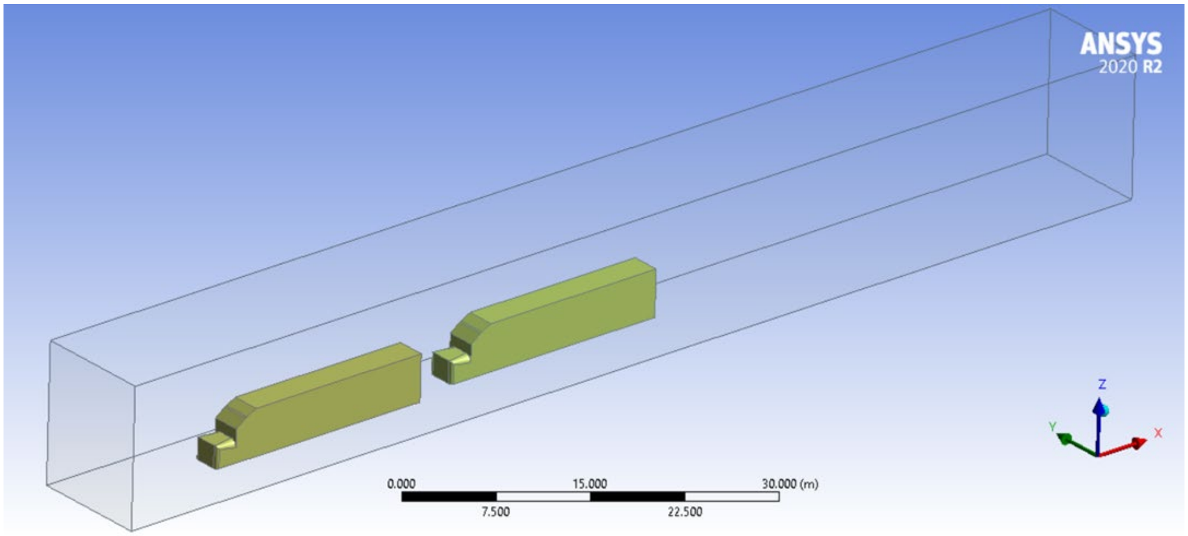


Figure 11. 3D model of the parametric two-truck platoon.

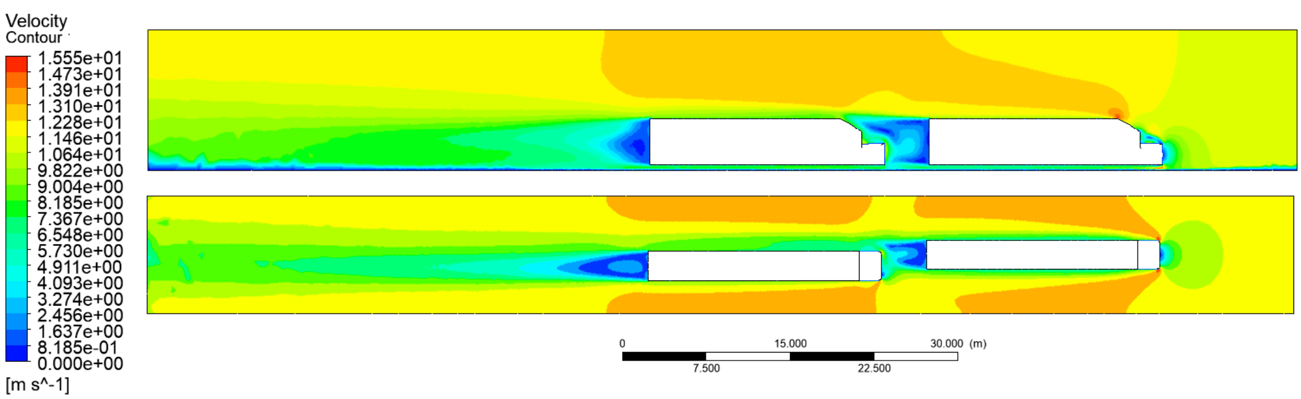


Figure 12. Sample velocity fields (side and top views).

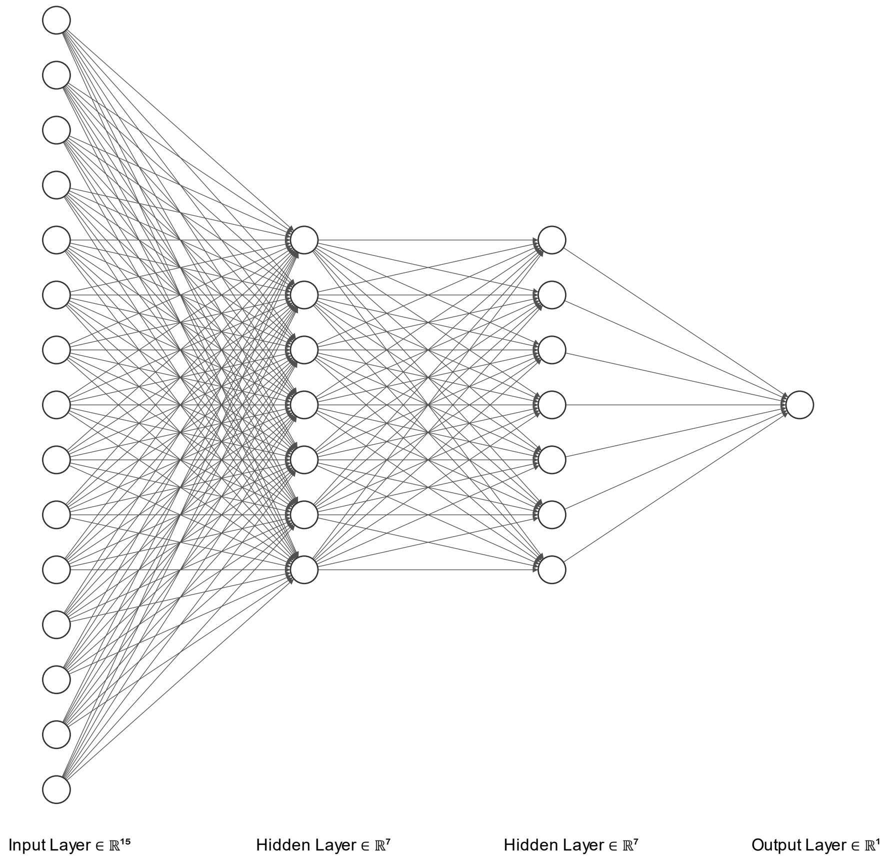


Figure 13. The dense neural network architecture for predicting the total drag forces of a two-truck platoon. Note that hidden layers are followed by a ReLU function. The network inputs are the 15 independent parameters mentioned in Figure 10, and the output is the total drag force.

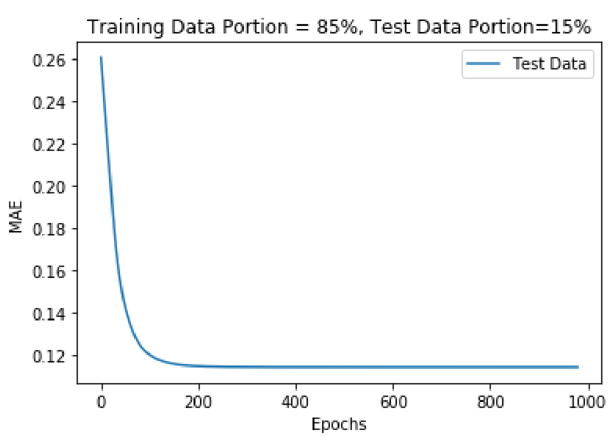


Figure 14. Mean absolute error (MAE) of the trained data-driven CFD model that predicts the overall drag force of two-truck platoon system. The hyperparameters are as follows: learning rate = 1e-4 and minibatch size = 32.

CASE 2: Five-Body Platoon

CFD analysis of multi-body platoons becomes extremely computationally expensive when the number of trucks increases. Therefore, in the first step, rectangular cubes are considered instead of the parametric truck in the previous section. The input parameters for the model and a sample velocity field from transient CFD analysis are presented in Figures 15-16. The output of the model includes five drag forces for each body, predicted using a dense deep neural network (Figure 17) trained on a dataset of 100 samples. As shown in Figure 18, an accuracy of about 85% is achieved for this prediction. Sample drag forces for transient analysis of the bodies can be seen in Figure 19.

```
height = round(unif(3.5,5), 2)
length = round(unif(8,23), 2)
width = round(unif(2.4,2.6),2)

headway1 = (length+round(unif(5,30)*Bool[0], 2))
headway2 = (length+round(unif(5,30)*Bool[1], 2))
headway3 = (length+round(unif(5,30)*Bool[2], 2))
headway4 = (length+round(unif(5,30)*Bool[3], 2))

lateral0 = round(unif(-halfwidth,halfwidth), 2)
lateral1 = round(unif(-halfwidth,halfwidth), 2)
lateral2 = round(unif(-halfwidth,halfwidth), 2)
lateral3 = round(unif(-halfwidth,halfwidth), 2)
lateral4 = round(unif(-halfwidth,halfwidth), 2)

angle = round(unif(0,30), 2)
velocity = round(unif(20.1168,33.528),2)
```

Figure 15. Parameters of the five-body platoon. Units are SI.

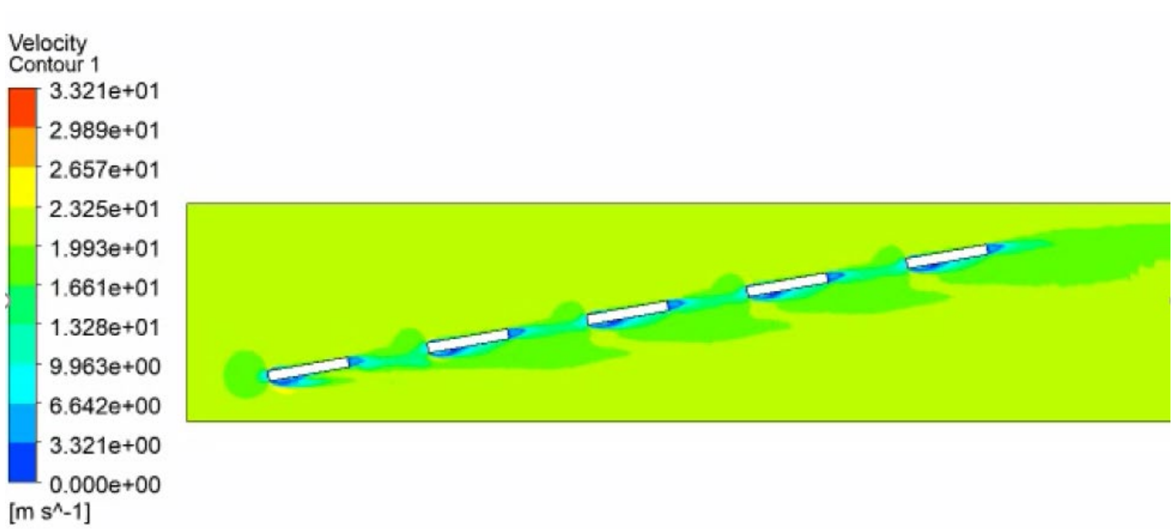


Figure 16. Sample velocity field (top view).

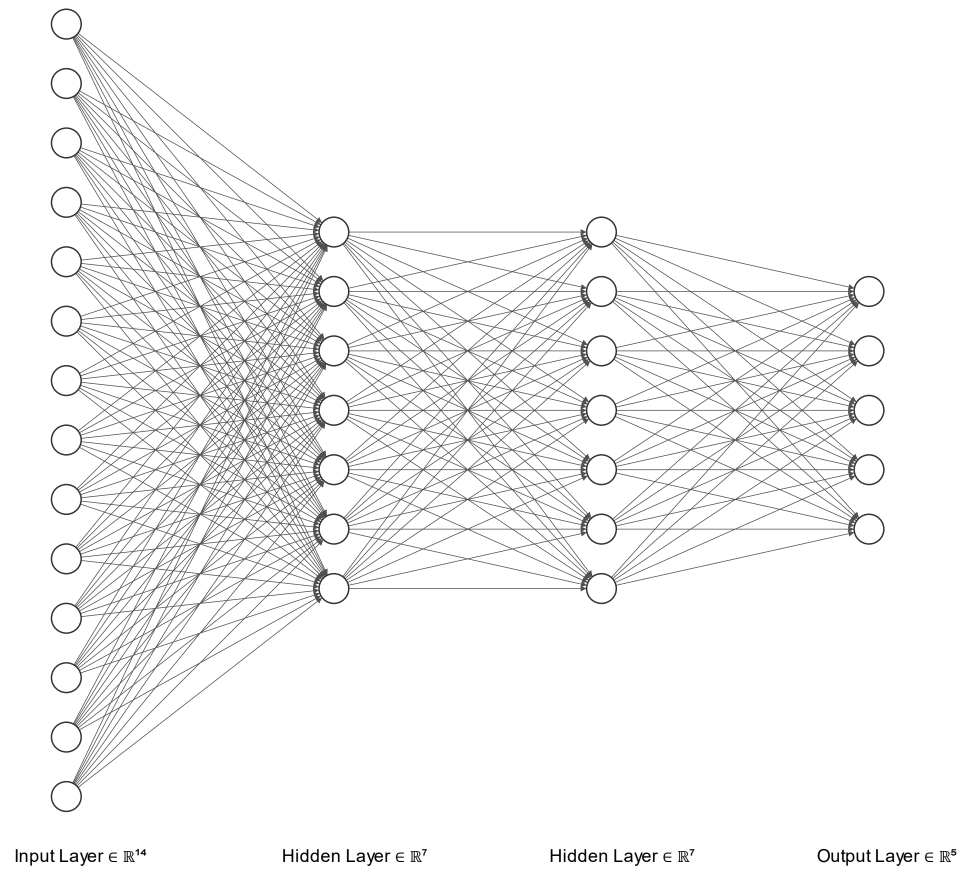


Figure 17. The dense neural network architecture for predicting the drag forces of five-body platoons. Note that hidden layers are followed by a ReLU function. The network inputs are the 14 parameters mentioned in Figure 15, and the outputs are five drag force values.

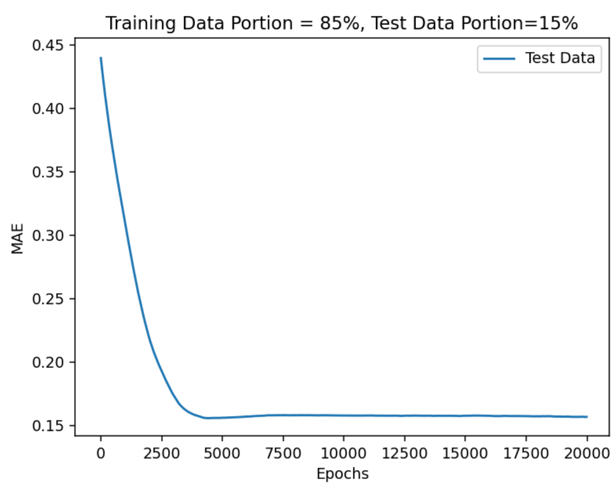
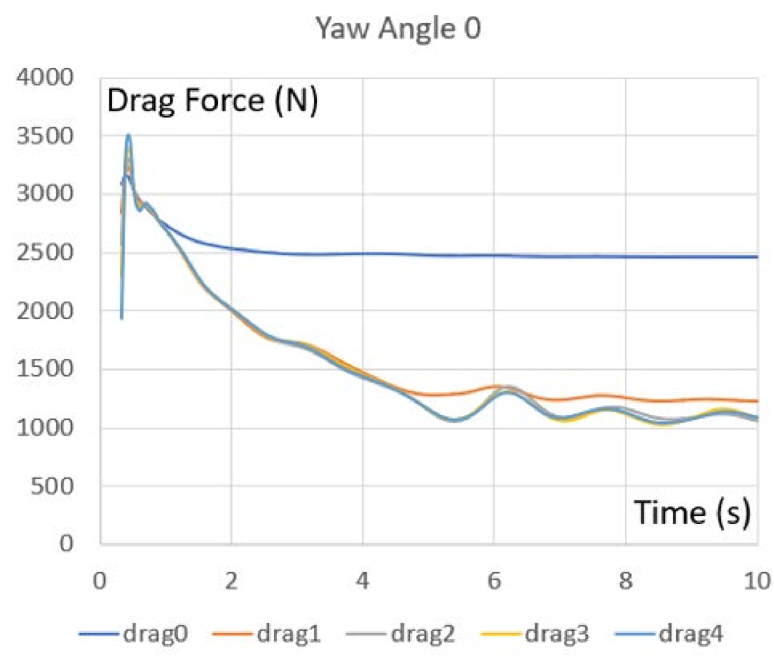
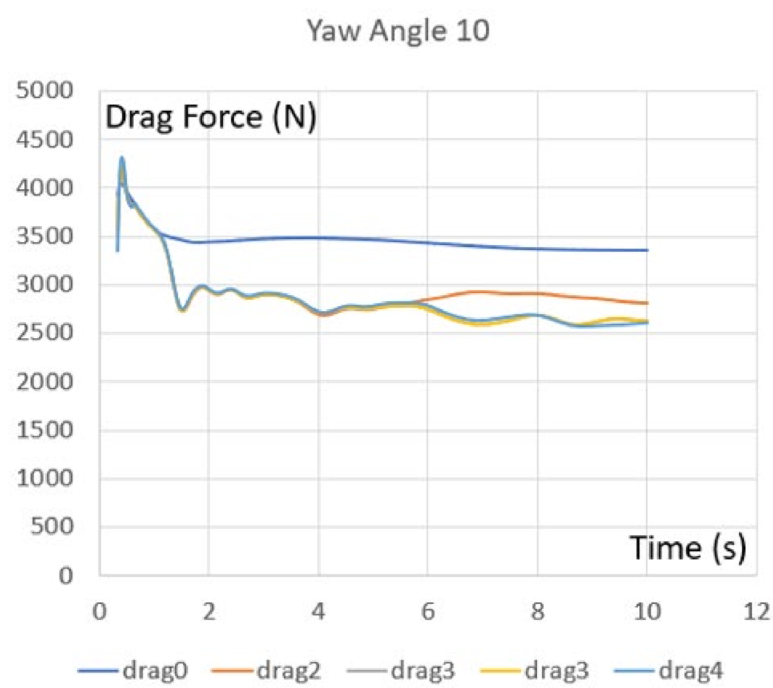


Figure 18. Mean absolute error (MAE) of the trained data-driven CFD model, which predicts the drag forces of a five-body platoon system. The hyperparameters are as follows: learning rate = 1e-4 and minibatch size = 16.



(a)



(b)

Figure 19. Comparison of drag forces at different angles of attack (yaw angles) (a) 0 and (b) 10 degrees for a speed of 45 mi/hr. The leading object is indexed as 0; and followers are 1 to 4, respectively. The drag-force values increase as the yaw angle is increased from 0 to 10 degrees.

SUMMARY AND FUTURE WORK

We investigated the learnability of neural network surrogate models used for the prediction of drag forces on trucks in a platoon. In particular, we developed and studied two models: (1) a parametric two-truck platoon and (2) a parametric five-body platoon with rectangular cubes as bodies. Even with limited data points (1,000 training data for the first model and 100 data points for the second model), the drag force is predicted with an accuracy of over 85%. As the next step, a model will be developed to combine the drag predictors of a simplified multi-body platoon and a single parametric truck. Such an insightful model can modularize bodies and address the effect of adding bodies on the drag forces of the system under parameters' variability and uncertainty.

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