Available online at www.academicpaper.org
Academic @ Paper
ISSN 2146-9067
International Journal of Automotive Engineering and Technologies
Vol. 5, Issue 4, pp. 168 – 175, 2016

International Journal of Automotive Engineering and Technologies
http://www.academicpaper.org/index.php/IJAET

Original Research Article

Drag Force Estimation of a Truck Trailer Model Using Artificial Neural Network

Mustafa Sarıoğlu[a], Mehmet Seyhan[a], Yahya Erkan Akansu[b*]

[a]Karadeniz Technical University, Faculty of Engineering, Mechanical Engineering Department, 61080, Trabzon, Turkey
[b]Ömer Halisdemir University, Faculty of Engineering, Mechanical Engineering Department , 51240, Niğde, Turkey

Received 24 October 2016 Accepted 24 December 2016

Abstract

Prediction of the drag forces acting on a truck trailer with/without spoiler is carried out by using artificial neural network (ANN). ANN model data set include the experiments of spoiler positions which have zero level to trailer front corner, -2 mm, -4.5 mm, -9 mm, +4.5 mm and +9 mm and truck trailer without spoiler. The experiments were carried out in the wind tunnel in the range of the free stream velocity between 4.6 m/s and 19.3 m/s, corresponding the *Re* number range, 1.0×10^5 -5.0×10^5. Mean absolute percentage error (MAPE) for training, validation and testing is 2.24%, 3.75% and 4.58% in the prediction of the drag forces, respectively. Prediction performance of the developed ANN model has a very good accuracy. According to the drag coefficients results, Reynolds number independence for truck trailer model is obtained at Reynolds number between 1.97×10^5 and 4.89×10^5. For spoiler position cases, while minimum drag coefficient acting on truck trailer with spoiler is seen at – 2mm offset, maximum drag coefficient is seen at -9 mm offset.

Keywords: Drag force, Truck trailer, Artificial neural network.

Nomenclature

AFC	Active flow control,
A_{fr}	Frontal area of the truck trailer model
ANN	Artificial neural network,
b	Bias value of input,
C_D	Drag coefficient,
d	Deviation
DBD	Dielectric barrier discharge,
f	activation function,
F	Estimated value,
F_D	Drag force,
L	Length of truck trailer
MAPE	Mean absolute percentage error,
MLP	Multilayer perceptron,
MSE	Mean squared error,
PFC	Passive flow control,
P_i	Predicted value,
R	Regression,
Re	Reynolds number,
R_i	Real measuring value,
U_∞	Free stream velocity
v	Weight of output layer,
w	Weight of input layer,
x_i	input variables
μ	Dynamic viscosity
ρ	Density of the air
u_{C_D}	Uncertainty of the drag coefficient

*Corresponding author:
Tel: +90 3882252250
E-mail: akansu@nigde.edu.tr

1. Introduction

Drag reduction is important to reduce the fuel consumption at passenger car and truck trailer therefore drag reduction leads to decreased fuel expense of the freight industry and carbon emission at long term. In order to obtain the drag reductions of vehicles, buildings, circular cylinders and square cylinder in the flow, there are two different flow control methods that are active and passive flow control methods. In the active flow control (AFC) methods, which need external energy supply, devices such as synthetic jet [1,2], continues jet [3], dielectric barrier discharge (DBD) plasma actuator [4] and so forth can be used. Passive flow control (PFC) methods which require some geometrical modification over body including splitter plate [5–7], spoiler [8,9], passive air channel[8,9], boat tail (flap) [10,11] and so on. AFC methods have been taken interest by the researcher for vehicles. But such methods need energy this means that fuel consumption and air pollution increase. Therefore, researchers focus especially on PFC methods in order to control the flow past truck trailer because of some advantages such as no energy requirement, no moving part and robust. Available studies related truck trailer in literature will briefly be summarized following paragraphs.

Özel et al. [8] investigated different cases including passive air channel, three different redirector and spoiler for reduction of drag at *Re* = 15900 - 453000. They obtained as 23.15% at combination of spoiler, passive channel and redirector. Akansu et al. [9] extended the study of Ozel at al. [8] by designing different passive air channel. Their result indicated that drag reduction of combination of spoiler, new passive channel design and redirector is 25.58%. El-Alti et al. [10] carried out an experimental and numerical study using boat tail placed on the rear of 1:10 scaled model of VOLVO FH16. Their results showed that drag reduction is obtained up to 0.7% with flap. Raemdonck and Tooren [11] is also used boat tail having different slant angle and obtained drag reduction of 12%. Fourrie et al. [12] investigated the effect of deflector placed behind Ahmet body by using particle image velocimetry (PIV) at $Re = 3.1 - 7.7\times10^5$. They obtained 9% drag reduction. For tractor trailer model with boat tail, Lanser et al. [13] and Khalinghi et al. [14] reduced drag up to 10% and 20%, respectively. Bayındırlı et al. [15] conducted to an experimental study for truck trailer by measuring pressure and force at *Re* = 117000 – 844000. Their results showed that trailer placed behind the truck increased drag coefficient from 0.608 to 0.704 when compared with the alone truck. Bayındırlı et al. [16] numerically investigated effect of aerodynamic forces over truck trailer model at *Re* = 59000 – 844000.

In order to decrease the number of required experiments such as force and pressure measurement at wind tunnel and develop closed/opened loop control system, artificial neural network (ANN) has a promising potential because of substantially superior learning ability for models varied linear/nonlinear. As defined by Bishop [17], artificial neural network is inspired from human neural network. A neural network can be considered as a non-linear mathematical function which provided a connection between input and output variables. ANN model is developed for prediction at wide range research area including car fuel consumption [18], airfoil aerodynamic force [19], decreasing the number of wind tunnel test [20], flight test data estimation [21], aircraft control design [22] and so forth. Wu and Liu [18] investigated prediction performance of ANN model for car fuel consumption. Engine style, weight of car, type of car, transmission types and car brand has been used as an input parameter in ANN model. Their results showed that developed ANN model is satisfactory for prediction of fuel consumption. Kurtulus [19] studied to estimate the drag and lift coefficient of NACA 0012 airfoil with the help of developed ANN model. Input parameters of their ANN model are translational velocity, translation displacement, attack angle and angular velocity. This coefficient estimation indicated that ANN model has good ability for flapping airfoil. In the study of Ross et al. [20], ANN is used in order to reduce required wind tunnel tests at a new airplane design. Input variables of ANN model are leading edge flap angle, trailing edge flap angle and attack angle. They predicted lift, drag and pitching moment coefficient and lift to drag ratio, separately by using the input variables. They indicated that ANN had very good estimation accuracy when compared with the experimental results.

Aim of this paper is to predict drag force acting on a truck trailer model with/without spoiler by means of ANN and reveal prediction ability of ANN for this case. Effects of spoiler placed over truck in terms of drag reduction are investigated at six different spoiler positions.

2. Experimental Setup

Experiments were carried out at a suction type wind tunnel having 57 cm × 57 cm of square test section at velocity of air having 4.6, 6.2, 7.8, 9.4, 11, 12.6, 14.2, 15.8, 17.45 and 19.3 m/s. 1/32 scaled truck trailer model and spoiler are used as in Özel et al. [8] and Akansu et al. [9]. As shown in Fig. 1, a spoiler placed over the truck has 6 different positions as an experimental parameter. Zero, -9mm and +9 mm positions of spoiler are just given as an example in Fig. 1. These six different positions of the spoiler are -9 mm, -4.5 mm, -2 mm, zero, +4.5 mm and +9 mm. Force measurements were performed with the help of a six axis ATI Gamma DAQ F/T load cell at aforementioned ten different velocity. Force measurement data were collected as 5000 sample at sampling frequency 500 Hz. More details of measurement system and specifications of the model can be seen in Özel et al. [8] and Akansu et al. [9].

Uncertainty analysis method is described in Eq.(1) by Coleman and Steele [23] in their book.

Uncertainty of the drag coefficient can be expressed in Eq. (2) like in the study of Bayındırlı et al.. [15] and Akansu et al. [9] by editing Eq. (1).

$$u_r = \left[a^2\left(\frac{u_{x_1}}{X_1}\right)^2 + b^2\left(\frac{u_{x_2}}{X_2}\right)^2 + c^2\left(\frac{u_{x_3}}{X_3}\right)^2 + \dots\right]^{1/2} \quad (1)$$

$$u_{C_D} = \frac{d_{C_D}}{C_D} = \left[(1)^2\left(\frac{d_{F_D}}{F_D}\right)^2 + (-1)^2\left(\frac{d_\rho}{\rho}\right)^2 + (-2)^2\left(\frac{d_{U\infty}}{U_\infty}\right)^2 + (-1)^2\left(\frac{d_{A_{fr}}}{A_{fr}}\right)^2\right]^{1/2} \quad (2)$$

where, u_{C_D} is total uncertainty of the drag coefficient, C_D is drag coefficient, d is deviation, F_D is drag force, ρ is density of the air, U_∞ is free stream velocity, A_{fr} is the frontal area of the truck trailer model. For *Re* = 4.89×10^5, the uncertainty of the drag coefficient is calculated as 6.8%.

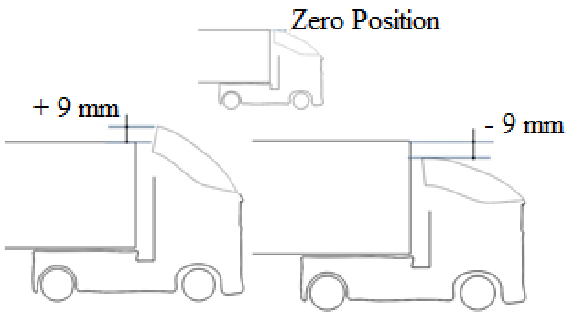

Fig. 1. Schematic view of truck trailer with spoiler having different positions

In order to obtain the relationship between the prototype and the real model, similarity including geometric, kinematic and dynamic must be provided. In this study, the geometric similarity was provided by using 1/32 scaled truck trailer model. For the kinematic similarity, blockage ratio is key parameter. The blockage ratio can be expressed as the ratio of truck-trailer frontal area to cross section area of the wind tunnel test section. As suggested in the study of Özel et al. [8] and Akansu et al. [9], blockage ratio must be smaller than 7.5%. In the present study, the blockage ratio is equal to 3.63% for +9 mm spoiler position having a greater frontal area that the other. Therefore, kinematic similarity is validated by providing the uniform velocity profile acting on the model by using flat plate over 8cm from the wind tunnel wall except moving surface for the ground effect.

Reynolds number can be defined as in Eq. (3)

$$Re = \frac{\rho L U_\infty}{\mu} \quad (3)$$

here, Re is the Reynolds number, L is the total length of the truck-trailer model, μ is the dynamic viscosity, U_∞ is the free stream velocity and ρ is the density of the air. For the dynamic similarity, it is necessary for the Reynolds number independence between real and prototype. As seen in Fig. 5, Reynolds number independence is provided at Re between 1.97×10^5 and 4.89×10^5 because the drag coefficient is nearly constant. This means that the dynamic similarity is valid for these Reynolds number ranges.

3. Artificial Neural Network

Artificial neural network which is inspired from biological neural network is composed of input variables such as weight, bias, activation function and output. For the neuron, bias (b) and weight (w) can be adjustable with a relation between input and output variable. Given ANN model structure in Fig. 2 is known as Multilayer perceptron (MLP). As shown in Fig. 2, Multilayer perceptron consist of three layers that are input, hidden and output layer. Output value can be calculated below;

$$F=f\left(a+\sum_{j=1}^{10} v_j \left[\sum_{i=1}^{4} g\left(w_{ij}x_i + b_j\right)\right]\right) \quad (4)$$

here, F is estimated value , a is the bias value for output, v_j is the weight of output value, w_{ij} is the weight of input layer, b is the bias value for input and x_i is input variable. f and g are the activation function for input and output layer, respectively.
Input variables for the developing ANN model are determined as velocity, frontal area of truck trailer model, total height of truck trailer with spoiler and given number for each model having different height. By using these input variables, drag forces acting truck trailer are predicted for aforementioned cases. Total 70 input data is used in order to train, validate and test. These input data is divided as 70% training, 15% validation and 15% test. As an activation function, S-shape sigmoid is used to train the ANN model. S-shape sigmoid activation function is express as in Eq. (5).

$$f(a) = \frac{1}{1+e^{-a}} \quad (5)$$

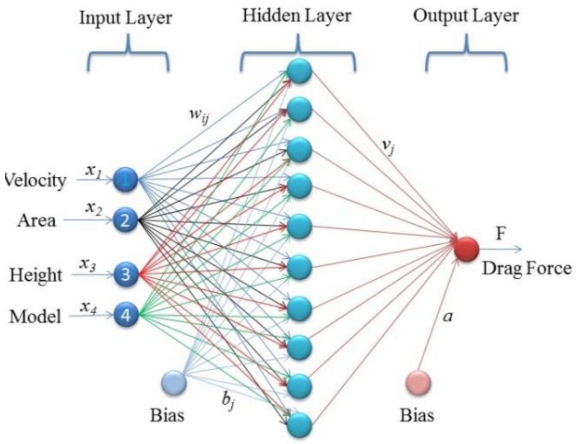

Fig. 2. Build ANN model structure.

Training algorithm is utilized Levenberg-Marquardt back propagation method. This algorithm is commonly used in literature by Wu and Liu [18], Kurtulus [19], Ross et al. [20] and Paksoy and Aradag [25].
In order to determine the performance of developed ANN model, mean squared error (MSE) and mean absolute percentage error (MAPE) are employed. MSE and MAPE can be defined as;

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(R_i - P_i)^2 \quad (6)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|R_i - P_i|}{R_i}\right)^2 x100 \quad (7)$$

Here n is the number of measurement data, R_i is real measuring value and P_i is the predicted value.

4. Result and Discussion

For truck and trailer without spoiler and with different spoiler positions that are zero, -2 mm, -4.5 mm, -9 mm, +4.5 mm and +9 mm, drag force measurement results are presented by reproducing with the help of ANN model at 4.6, 6.2, 7.8, 9.4, 11, 12.6, 14.2, 15.8, 17.45 and 19.3 m/s. MAPE, MSE and regression (R) values are given in order to evaluate the prediction performance of developed ANN model including training, validation and testing sections in table 1. As mentioned by Lewis[26], if MAPE is smaller than 10%, prediction evaluation is high accuracy. When examined Table 1. MAPE values for training, validation and testing are 2.24%, 3.75% and 4.58%, respectively. This means that the developed ANN model has high accuracy. It should be noted that if R and MSE is equal or very close to 1 (for *R*) and 0 (for MSE), respectively, prediction performances are very good. MSE for training, validation and testing is nearly equal to zero, therefore, error between actual and predicted value has scarcely any. Regression value indicates relationship between measured and predicted drag force. Variation of regression values of training, validation and test is plotted in Fig. 3. Training, validation and testing values of R is nearly 1. That is, developed ANN model shows a good agreement with measured drag forces.

Table 1. Prediction performance of developed ANN model in drag force acting on truck trailer

	Training	Validation	Testing
MAPE	2.24%	3.75%	4.58%
MSE	5.468×10^{-5}	2.546×10^{-4}	1.02×10^{-4}
R	0.999831	0.999713	0.99946

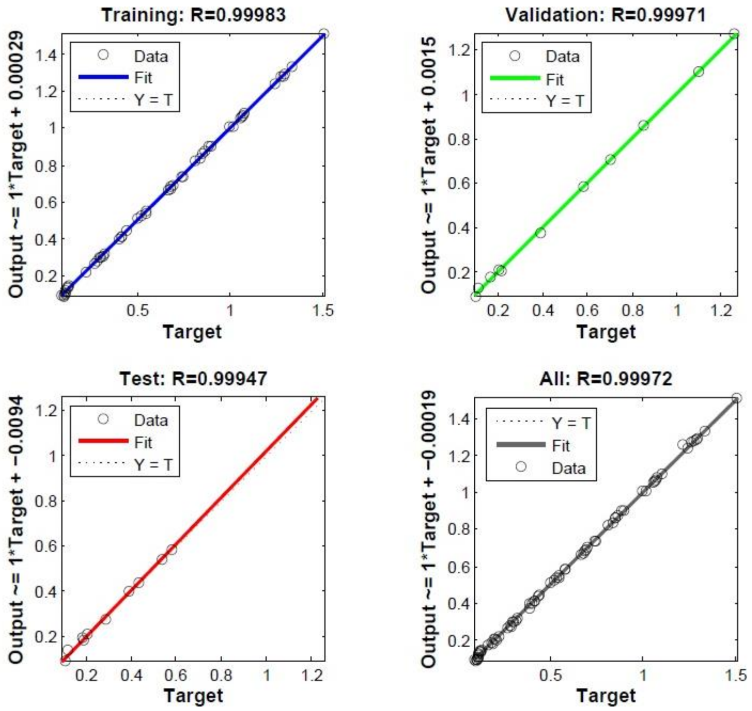

Fig. 3. Relationship between measured and estimated values for training, validation and test.

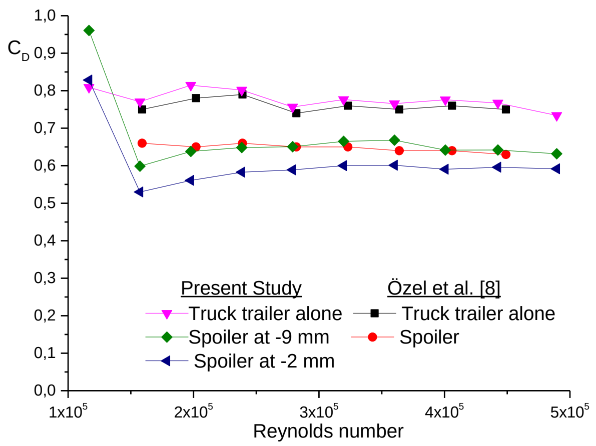

Fig. 4. Comparison of the variations of C_D as a function of the Reynolds number

Variation of C_D as a function of the Reynolds number is given in Fig. 4 by comparing the present study and the study of Özel et al. [8]. The results of the present study exhibit similar trend with that of Özel et al. [8] for truck trailer with/without spoiler cases. Özel et al. [8] didn't take into account the position of spoiler but the results of their spoiler position show a good agreement with that of the spoiler position of the present study at -9 mm. Özel et al. [8] used worst spoiler position when compared with the present study. C_D for the studies of the present and

Özel et al. [8] is 0.6 at $Re = 3.2\times10^5$ and 0.65 at $Re = 3.23\times10^5$, respectively. Fig. 5 shows the comparison of measurement and predicted drag forces as a function of the velocity. These figures indicate that predicted drag values via developed ANN model shows nearly similar trend with measurement results.

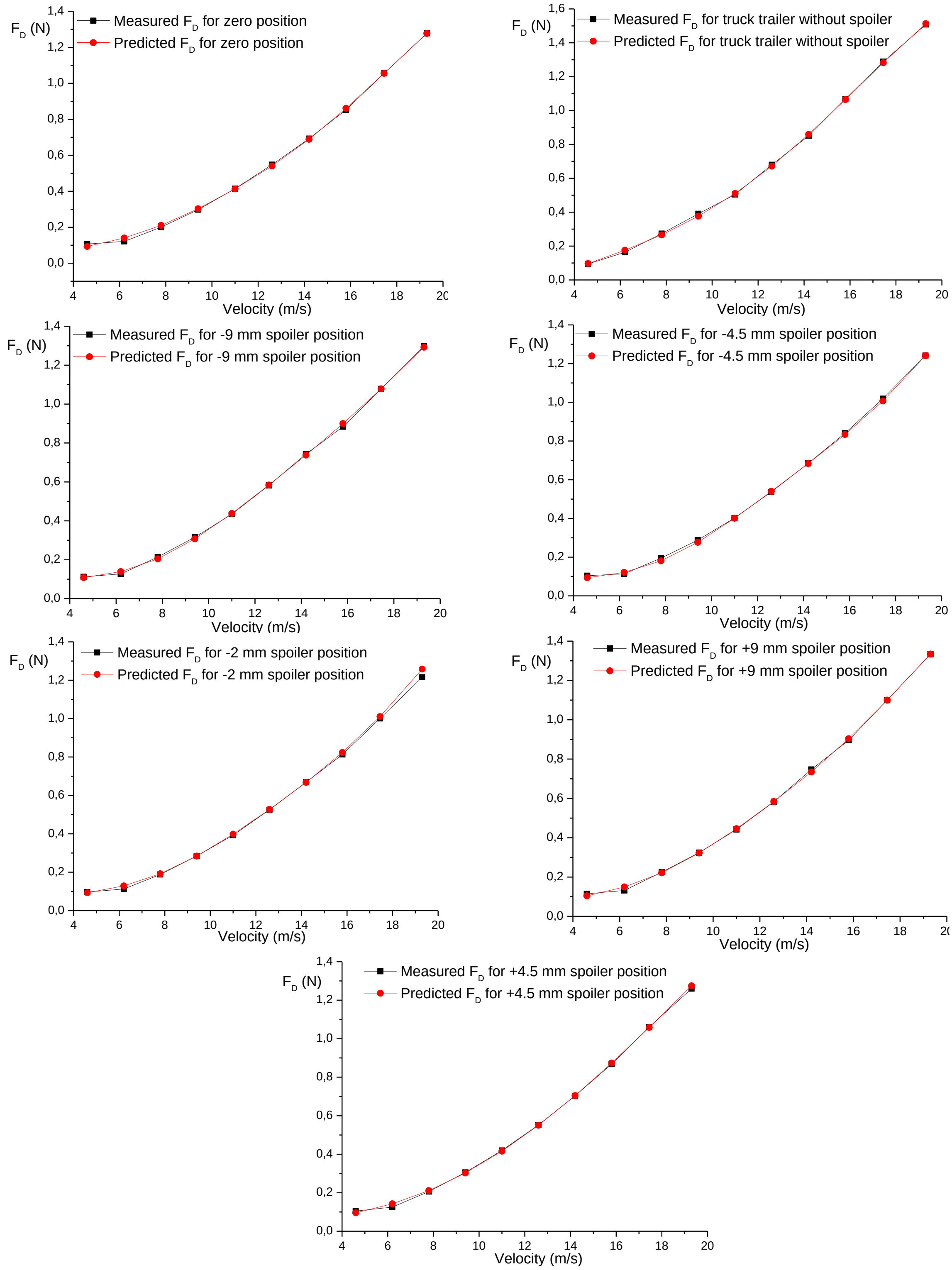

Fig. 5. Comparison of measurement and predicted of the drag force for zero, -2 mm, -4.5 mm, -9 mm +4.5 mm and +9 mm spoiler positions and truck trailer without spoiler.

The variation of drag coefficient (C_D) with Reynolds number is plotted for comparison between experimental results and prediction in Fig. 6. Straight lines represent the drag coefficients of the experimental results while dash lines denote calculated drag coefficients from the predicted drag forces. At -2 mm spoiler position, the drag reduction is obtained as 22.6% at Re = 3.2×10^5 when compared with the truck trailer without spoiler. For -9 mm spoiler position, the drag coefficient is higher than those of the other spoiler positions from Re = 1.97×10^5 to 4.89×10^5. It can be say that there is a very low Reynolds number dependence at the Reynolds number between 1.97×10^5 and 4.89×10^5.

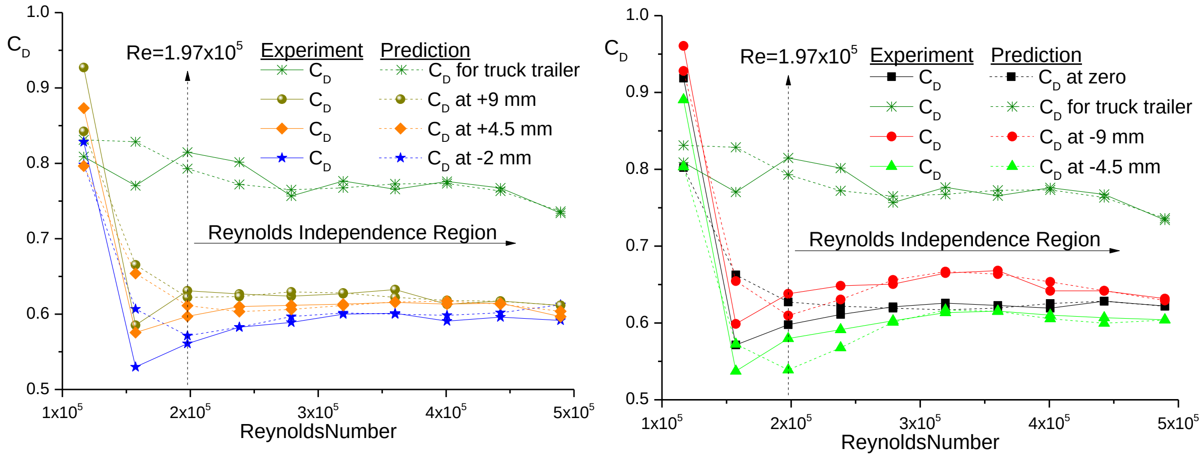

Fig. 6. Variation of the drag coefficient as a function of Re for truck and trailer with spoiler

5. Conclusion

An experimental study was carried out to measure the drag forces acting on truck trailer for different cases including spoiler positions at 4.6, 6.2, 7.8, 9.4, 11, 12.6, 14.2, 15.8, 17.45 and 19.3 m/s. In order to predict the drag forces divided randomly training, validation and testing, artificial neural network model is developed. MAPE value has 2.24% for training, 3.75% for validation and 4.58% for testing. Prediction performance of the developed ANN model has very good accuracy. The results indicated that ANN can be successfully used in an aerodynamic application in order to reduce the number of experiment. Drag reduction is obtained as 22.6% for -2mm spoiler position. There is Reynolds independent at Reynolds number between 1.97×10^5 and 4.89×10^5. Authors suggests that ANN model can be used to decrease the number of experiments by saving time and cost. Especially, the prediction of the intermediate values will be useful for the optimizations of the parameters, like the spoiler offset position.

Acknowledgments

The authors would like to acknowledge the financial support of this work by the Scientific Research Projects Unit (BAP) of Karadeniz Technical University with the contract number of 2007.112.003.2.

6. References

[1] M. Amitay, D.R. Smith, V. Kibens, D.E. Parekh, A. Glezer, "Aerodynamic flow control over an unconventional airfoil using synthetic jet actuators", AIAA J. Vol. 39, pp. 361–370, 2001.

[2] M. El-Alti, V. Chernoray, P. Kjellgren, L. Hjelm, L. Davidson, "Computations and full-scale tests of active flow control applied on a VOLVO truck-trailer in Aerodyn. Heavy Veh. III ", Springer International Publishing, Vol. 79, pp. 253–267, 2016.

[3] Y.E. Akansu, E. Fırat, "Control of flow around a square prism by slot jet injection from the rear surface", Exp. Therm. Fluid Sci., Vol. 34, pp. 906–914, 2010.

[4] Y.E. Akansu, F. Karakaya, A. Şanlısoy, "Active control of flow around naca 0015 airfoil by using DBD plasma actuator", EPJ Web Conf., Vol. 45, pp. 1008, 2013.

[5] Y.E. Akansu, M. Sarioglu, T. Yavuz, "Flow around a rotatable circular cylinder-plate body at subcritical Reynolds numbers",

AIAA J., Vol. 42, pp. 1073–1080, 2004.
[6] M. Sarioglu, Y.E. Akansu, T. Yavuz, "Flow around a rotatable square cylinder-plate body", AIAA J., Vol. 44, pp. 1065–1072, 2006.
[7] P. Gilliéron, A. Kourta, "Aerodynamic drag reduction by vertical splitter plates", Exp. Fluids., Vol.48, pp. 1–16, 2010.
[8] M. Özel, E. Aygün, Y.E. Akansu, C. Bayındırlı, M. Seyhan, The passive flow control around a truck-trailer model / Bir kamyon römork modeli etrafındaki pasif akış kontrolü, Int. J. Automot. Eng. Technol., Vol. 4, Issue 4, pp. 185-192, 2016.
[9] Y.E. Akansu, C. Bayindirli, M. Seyhan, "The improvement of drag force on a truck trailer vehicle by passive flow control methods", Journal Therm. Sci. Technol., Vol. 36, pp. 133–141, 2016.
[10] M. El-Alti, V. Chernoray, M. Jahanmiri, L. Davidson, "Experimental and computational studies of active flow control on a model truck-trailer", EPJ Web Conf., Vol. 25, pp. 01012, 2012.
[11] G.M.R. Van Raemdonck, M.J.L. Van Tooren, "Numerical and Wind Tunnel Analysis Together with Road Test of Aerodynamic Add-Ons for Trailers in Aerodyn. Heavy Veh. III", Springer International Publishing, Vol. 79, pp. 237–252, 2016.
[12] G. Fourrié, L. Keirsbulck, L. Labraga, P. Gilliéron, "Bluff-body drag reduction using a deflector", Exp. Fluids., Vol. 50, pp. 385–395, 2011.
[13] W.R. Lanser, J.C. Ross, A.E. Kaufman, "Aerodynamic Performance of a Drag Reduction Device on a Full-Scale Tractor/Trailer", SAE Technical Paper, 1991.
[14] B. Khalighi, S. Zhang, C. Koromilas, S.R. Balkanyi, L.P. Bernal, G. Iaccarino, P. Moin, "Experimental and Computational Study of Unsteady Wake Flow Behind a Bluff Body with a Drag Reduction Device", SAE Technical Paper, 2001.
[15] C. Bayındırlı, Y.E. Akansu, M.S. Salman, The Determination Of Aerodynamic Drag Coefficient Of Truck and Trailer Model By Wind Tunnel Tests, Int. J. Automot. Eng. Technol. Vol. 5, Issue 2, pp. 56-60, 2016.
[16] C. Bayındırlı, Y.E. Akansu, M.S. Salman, D. Çolak, "The Numerical Investigation of Aerodynamic Structures of Truck and Trailer Combinations", Int. J. Automot. Eng. Technol. Vol. 4, Issue 3, pp. 139-145, 2015.
[17] C.M. Bishop, Neural networks and their applications, Rev. Sci. Instrum. Vol. 65, pp. 1803–1832, 1994.
[18] J.-D. Wu, J.-C. Liu, "Development of a predictive system for car fuel consumption using an artificial neural network", Expert Syst. Appl., Vol. 38, pp. 4967–4971, 2011.
[19] D.F. Kurtulus, "Ability to forecast unsteady aerodynamic forces of flapping airfoils by artificial neural network", Neural Comput. Appl. Vol., 18, pp. 359–368, 2009.
[20] J.C. Ross, C.C. Jorgenson, M. Norgaard, Reducing wind tunnel data requirements using neural networks, (1997).
[21] R.L. McMillen, J.E. Steck, K. Rokhsaz, "Application of an artificial neural network as a flight test data estimator", J. Aircr. Vol. 32, pp. 1088–1094, 1995.
[22] C.M. Ha, "Neural Networks Approach to AIAA Aircraft Control Design Challenge", Vol. 18, 1995.
[23] H.W. Coleman, W.G. Steele, Experimentation, validation, and uncertainty analysis for engineers, John Wiley & Sons, 2009.
[24]A. Paksoy, S. Aradag, Artificial Neural Network based prediction of time-dependent behavior for lid-driven cavity flows, J. Therm. Sci. Technol., Vol. 35, pp. 1–18, 2015.
[25] C.D. Lewis, "Industrial and Business Forecasting Methods", Butterworth Scientific, London, 1982.