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Investigating the fluid-structure interaction of L-shaped pipe bends using machine learning

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Abstract. The fluid Structure interface is an important area of research for its challenges in fluid structure dynamics in understanding the effect of fluid on motion and deformation of structures. In the current study, we used the L-Shaped pipe bent and did a CFD simulation at the velocity inlet condition of the range 1-3 m/s with keeping adiabatic wall condition and environmental pressure at the outlet. The reason for choosing L-Shaped bent is that it creates a sharp change in the flow direction, which leads to complex vortices, turbulence and pressure distribution. It also puts a significant mechanical load on the structure due to this change in flow, resulting in a large structural deformation. The result of CFD simulation is used to do the structural simulations at different material types, lengths of both arms, keeping the diameter, angle and fillet radius of the bent at a constant value. The database created is then used as an input to the machine learning (ML) model to predict for an arbitrary material and at any length of the bent without doing all the simulations. The simulation results also help to co-relate the impact of variation in length with the bent's stress, strain and displacement.

Introduction

Fluid-structure dynamics refers to studying the interactions between fluid flow and structures. This is an important area of research in various fields, including engineering, physics, and biology. One of the key challenges in fluid structure dynamics is understanding how fluid flow can affect the motion and deformation of structures. This is particularly relevant in the design of aircraft, ships, and other vehicles that must withstand the forces of fluid flow.

One important tool for studying fluid-structure dynamics is computational fluid dynamics (CFD), which uses computer simulations to model the flow of fluids and their interactions with structures. CFD can provide valuable insights into the behavior of fluid-structure systems, allowing engineers to optimize designs and predict performance. Many factors can influence fluid-structure dynamics, including the shape and size of the structure, the properties of the fluid, and the flow conditions. Research in this area often involves developing mathematical models and computational methods to accurately predict the behavior of these systems.

The IB method, introduced by Charles Peskin in 1972, revolutionized the study of the interaction between flexible structures and viscous, incompressible fluids. The method, described in [1, 2], uses a fully coupled computational analysis that represents the fluid domain using an Eulerian mesh and the immersed structure using a Lagrangian grid. It employs the Dirac-delta function to transfer forces from the boundary to the fluid and velocity from the fluid to the boundary. Despite its limitations in only being applicable to flexible boundaries, researchers have made advancements in the method. Goldstein et al. [3] proposed a feedback forcing scheme to determine the fluid's external force, while Saiki & Biringen [4] used a discrete hat function for transfer of force and velocity information. Mohd-Yusof [5] took it further by creating a direct forcing formulation, eliminating the need for discrete functions or feedback forcing, using the

Materials Research Proceedings 31 (2023) 204-211 https://doi.org/10.21741/9781644902592-22

pseudo-spectral method. The IB method has also been applied to other areas, such as the analysis of blood clotting by Fogelson & Guy [6], where they modeled a fluid containing suspended platelets and included chemical reaction equations to study their response to stimuli.

Significant progress has been made in the field of fluid-structure interaction (FSI) by combining the Navier-Stokes (N-S) and Euler-Bernoulli (E-B) equations. These equations are utilized to model an incompressible fluid flow and a flexible immersed boundary respectively, as described in [7-10]. The N-S equations control the behavior of the fluid by considering mass and momentum conservation, while the E-B theory predicts small deflections of structures subjected to pointwise or distributed lateral loads. This theory is founded on a fourth-order differential equation that links the transverse displacement of a structure to the force applied to it. The major challenge in FSI lies in managing the N-S and E-B equations together. Energy transport between a beam-like structure and a Newtonian fluid is explored in [11]. Pontaza & Menon [12] introduced an FSI problem of a flexible pipe in a viscous fluid, modeled as an E-B beam, to determine its response to vortex-induced vibrations in the time domain.

Recently, the use of physics-guided machine learning (ML) approaches has become prevalent due to their ability to combine data-driven methods with physical knowledge to build descriptive models, carry out efficient simulations, and identify input-output relationships. For instance, deep neural networks (NNs) have been utilized to approximate partial differential equations by training on extensive datasets [13,14]. ML techniques have been explored in different areas such as structural dynamics, fluid mechanics, and FSI problems. In [15], recurrent NNs and multi-layer perceptrons were merged with domain knowledge to enhance structural dynamics simulations. For fluid domains with complex boundary conditions, a hybrid network, V2P-Net, was designed to predict pressure from observed velocity fields [15]. Furthermore, a novel hydro-elastic reduced order FSI model using ML was proposed to overcome instability issues associated with traditional Galerkin Projection method [15]. These works motivated the researchers to use ML to significantly decrease the computational cost in traditional FSI analysis.

In this analysis we use Deep learning method to predict the structural behaviors of a L-Shaped bend based on FSI analysis at different inlet flow rate, for the different upper as well as lower length and construction material.

Materials and methods

For the current study we use a L-shaped bend with the dimension of a 10 mm diameter, 25mm upper length and 50mm lower length with a fillet radius of 5 mm at the bent given by figure 1.

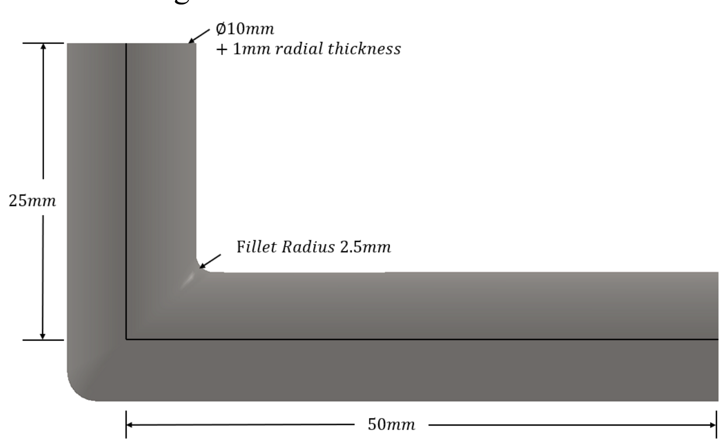


Figure 1: Dimension of L-Shaped Bent for FSI analysis

The FSI is achieved performing CFD analysis at first and then static structural analysis with pressure, temperature distribution as an external load. This FSI analysis is carried out for 15 different structural material (namely, SS 304, Alloy Steel, Plain Carbon Steel, ductile Iron, Grey Cast Iron, 1060 Aluminum Alloy, Aluminum Bronze, Brass, Copper, Manganese Bronze, Magnesium Alloy, Monel(R) 400, ABS, Nickel and PET) and a database is created by varying different upper, lower arm lengths and for different materials.

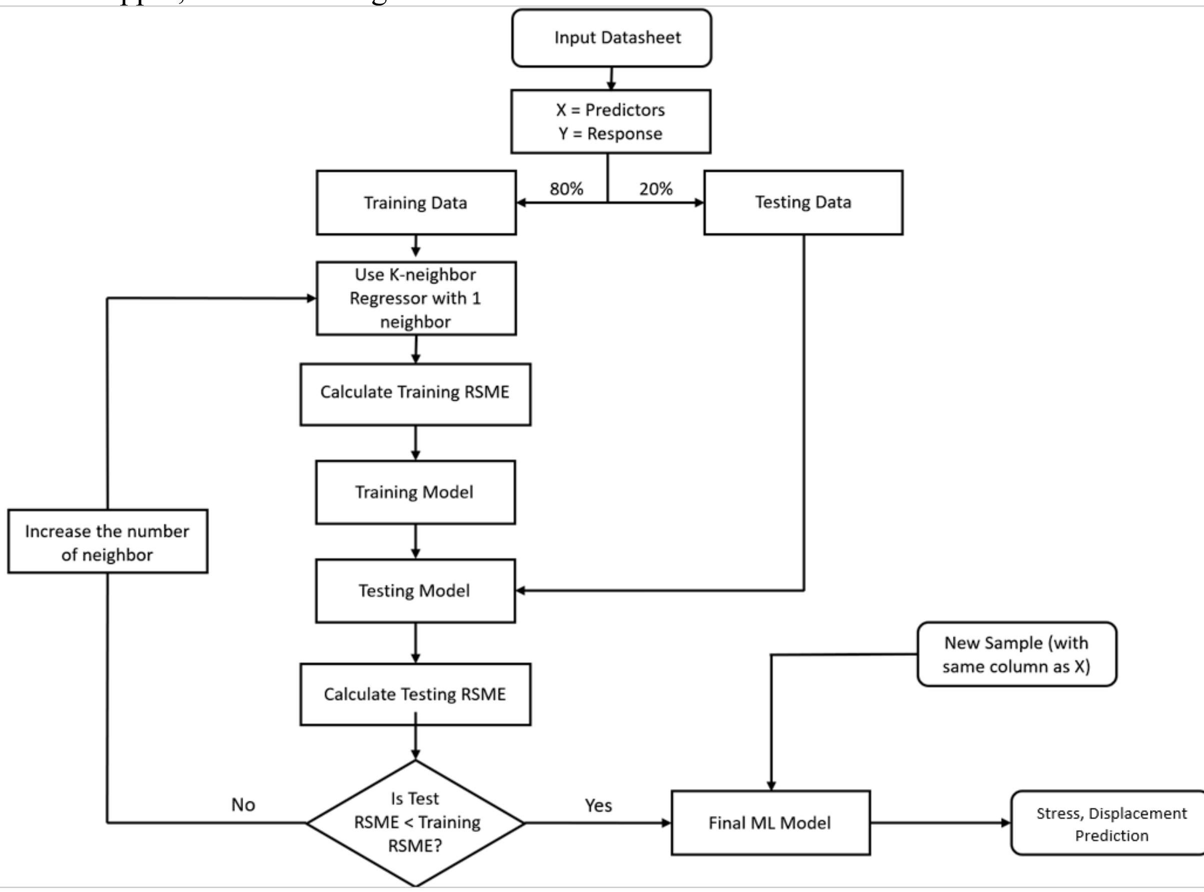


Figure 2: Algorithm for Investigating the FSI using Machine Learning

This database is use as input to the machine learning algorithm (KNN-Regressor) in python and with that the ML model will be able to predict the Stress and Displacement of bend for unknown material (alloy) by providing Young's Modulus and Poisson's ratio. Figure 2 explains the ML algorithm to predict the FSI results for the L-shaped bend with the of a flow chart. The predictor and response is selected and split in training and testing datasets using test_train_split python function. Training data is fed to KNN Regressor with 1 neighbour and then training and testing RMSE (Root Mean Squared Error) is calculated. If the $RMSE_{Test} < RMSE_{Training}$ then the model can be used for making prediction on new sample and if $RMSE_{Test} > RMSE_{Training}$ then the number of neighbors is increased until $RMSE_{Test} < RMSE_{Training}$. Now, the Stress and displacement of the bend is obtained with the new sample in the same sequence as that of predictor.

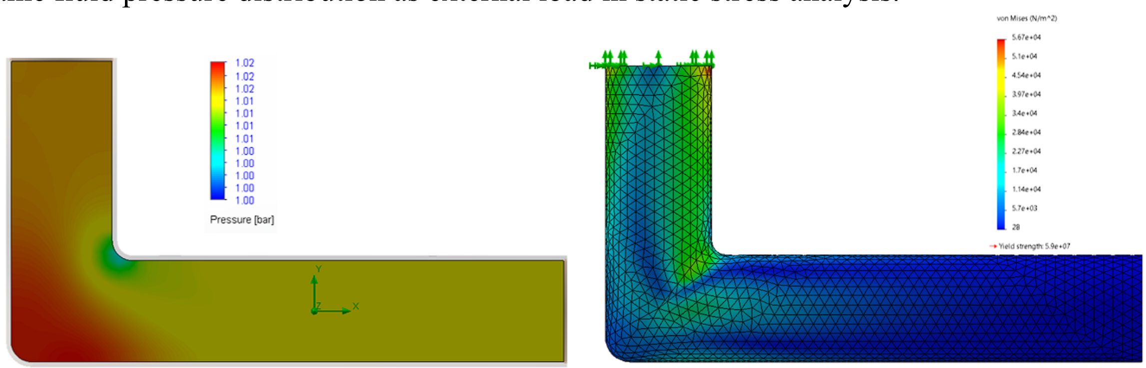
Results and discussion

To begin the FSI analysis the CFD simulation is done with the following conditions using SOLIDWORKS Flow simulation software:

Table 1: CFD simulation parameters

SL NO.	PARAMETER	VALUE
1.	Fluid Property	Water (20.5 ºC, 1 atm)
2.	Inlet velocity	1m/s, 2m/s
3.	Outlet Condition	1 atm (abs)
4.	Surface Roughness	0 micrometre
5.	Wall Condition	Adiabatic
6.	Mesh	15008

This Pressure distribution obtained for the pipe at the particular condition is imported to SolidWorks Simulation software, and constraining the upper length of the bend while keeping the lower length free, the static, steady-state simulation is executed with figure 2 showing fluid pressure distribution and Von-Misse Stress for 1m/s of fluid inlet condition and AISI SS 304 as pipe material. It is evident from the figure that the maximum fluid pressure is at the bent but for the static stress it is maximum at the fixed geometry and minimum at the free end with accounting the same fluid pressure distribution as external load in static stress analysis.



(a) (b)

Figure 2: Schematic diagram of CFD simulation (a. pressure distribution at 1m/s velocity input) and the respective static structural analysis (b. Von-Mises Stress distribution with the external load as pressure distribution from CFD simulation)

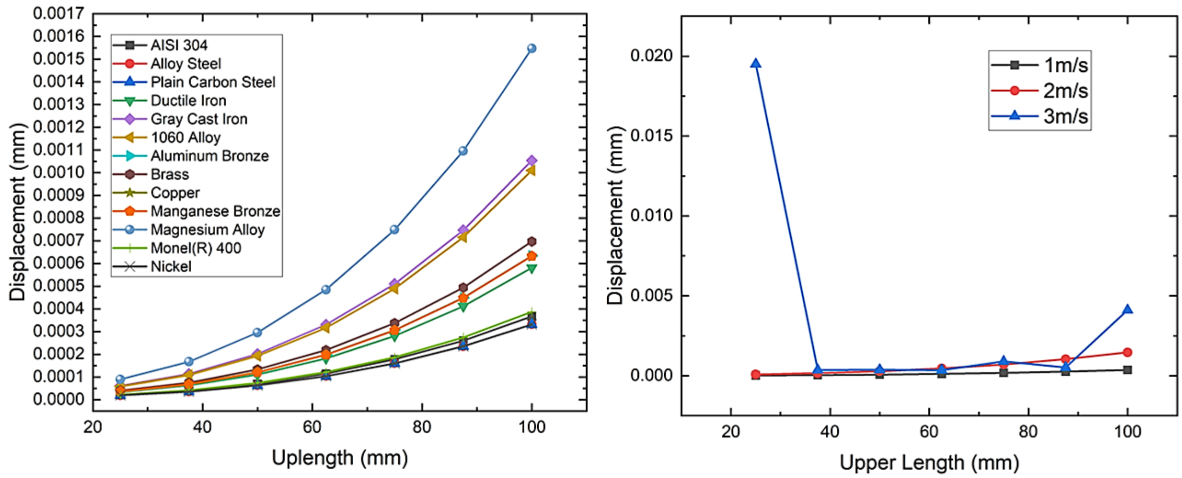
Table 2 shows the meshing result for static stress analysis for the initial geometry (i.e. upper length 25mm and lower length 50mm).

Table 2: Meshing result for static structural analysis

Static Structural Meshing Result	
Mesh Type	Solid Mesh
Mesher Used	Blended curvature-based mesh
Max Element size	1.14408mm
Min Element size	0.381356mm
Total Nodes	26056
Total Elements	12946
Max Aspect Ratio	6.0982

Figure 3 shows the variation of displacement for different material at 1m/s inlet velocity (figure 3 (a)) and the displacement for different inlet velocities with SS 304 and it can be seen that as the length increases the displacement also increases not linearly but quadratically (different quadratic function for different material).

Materials Research Proceedings 31 (2023) 204-211 https://doi.org/10.21741/9781644902592-22



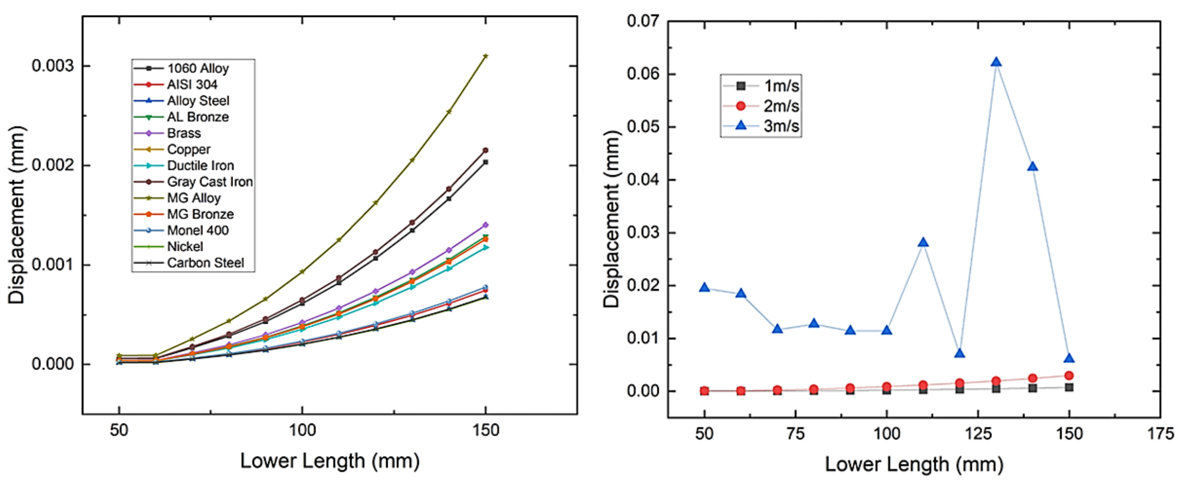
(a) **(b)**

Figure 3: Variation of displacement with upper arm length for different material (a), and for different inlet velocities with SS 304 material (b).

Figure 4 shows the variation in displacement with change in lower arm length for different materials as well as for different inlet velocities also. And it is evident from figure 3 and 4 that at inlet velocity of 3 m/s the pipe with SS304 goes to the plastic deformation (which is shown in figure 5) hence it is eliminated from inclusion in the database for Machine Learning predictions.

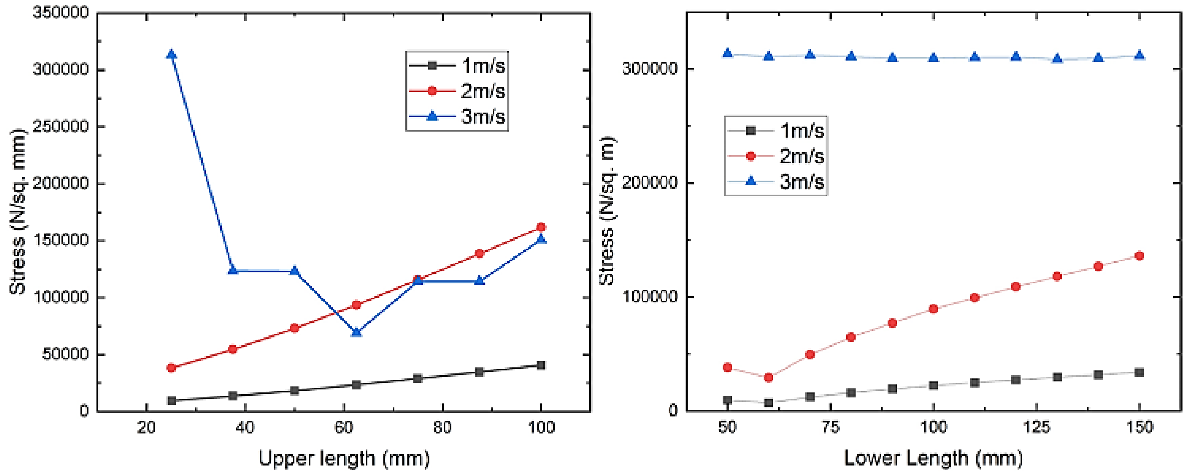
From figure 3 and 4 it is also concluded that the maximum and minimum displacement for Magnesium Alloy and Carbon Steel for both the cases i.e., upper arm length as well as lower arm length. The database is created by varying materials of construction (15 materials, namely Young's Modulus and Poisson's ratio), upper length (25-100mm) and lower length (50-150mm) and the respective Stress, Stain, Displacement. **Figure 6** shows a snapshot of the database with first 5 data points.

As for KNN Regression Machine learning method the input i.e. Predictors should be a numerical value so the we need to exclude the material column. Hence the predictors are "uplength, lowerlength, YM, PR and velocity" while the response for the model are "Displacement1 and Stress2".



(a) (b)

Figure 4: Variation of displacement with lower arm length for different material (a), and for different inlet velocities with SS 304 material (b).



(a) **(b)**

Figure 5: Variation in stress with (a) change in upper arm length, (b) change in lower arm length for SS304

	Material	uplength	lowerlength	YM	PR	Velocity	Displacement1	Stress2
0	1060 Alloy	25.0	50	66178000000	0.27	1	0.000059	9549
1	1060 Alloy	25.0	60	66178000000	0.27	1	0.000060	7294
2	1060 Alloy	25.0	70	66178000000	0.27	1	0.000169	12320
3	1060 Alloy	25.0	80	66178000000	0.27	1	0.000287	16110
4	1060 Alloy	25.0	90	66178000000	0.27	1	0.000432	19250

Figure 6: Snapshot of the database with first five data points for Jupiter notebook

$$X = \{uplenth, lowerlength, YM, PR, Velocity\}$$
$$Y = \{Displacement1, Stress2\}$$

In order to determine the best value of nearest neighbours using *for* loop the prediction with neighbours in range of 1 to 10 is executed and the neighbour with least Mean Absolute Percentage Error (MAPE) is chosen. Figure 7 shows the values of MAPE with different neighbours and according to this the nearest neighbour of 4 is chosen for our model. Taking KNN Regressor with 4 Nearest-Neighbours the testing and the training MAPE and R2 Value is shown in table 3 and from that it is evident that our ML model is a very good match for the current scenario and will show a very good prediction.

Table 3: Training and Testing MAPE and R^2 Value with 4 neighbour KNN Regressor

Training		Testing	
MAPE	0.11	MAPE	0.155
R^2 Value	0.9848	R^2 Value	0.9769

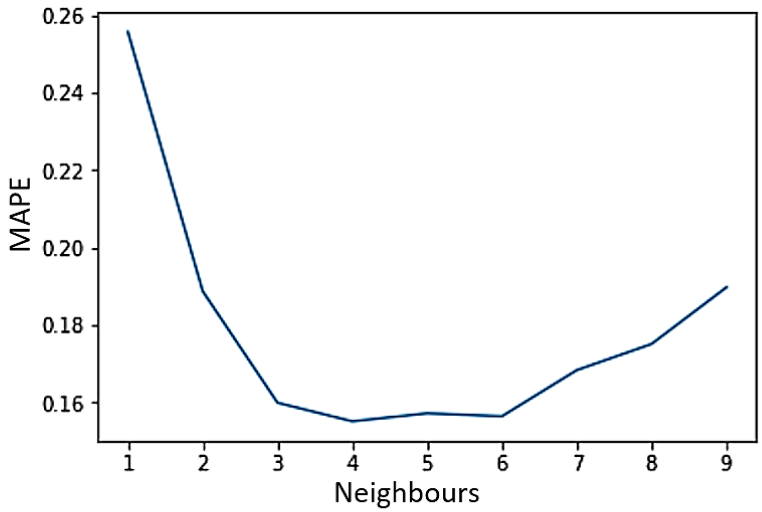


Figure 7: Mean Absolute Percentage Error (MAPE) for different neighbours.

Based on the accuracy of the KNN- Regression model a plot is created showing the comparison between original and the predicted values of stress and displacement for ABS material and keeping upper length as constant at 50mm as shown in figure 8 and the results are quite impressive.

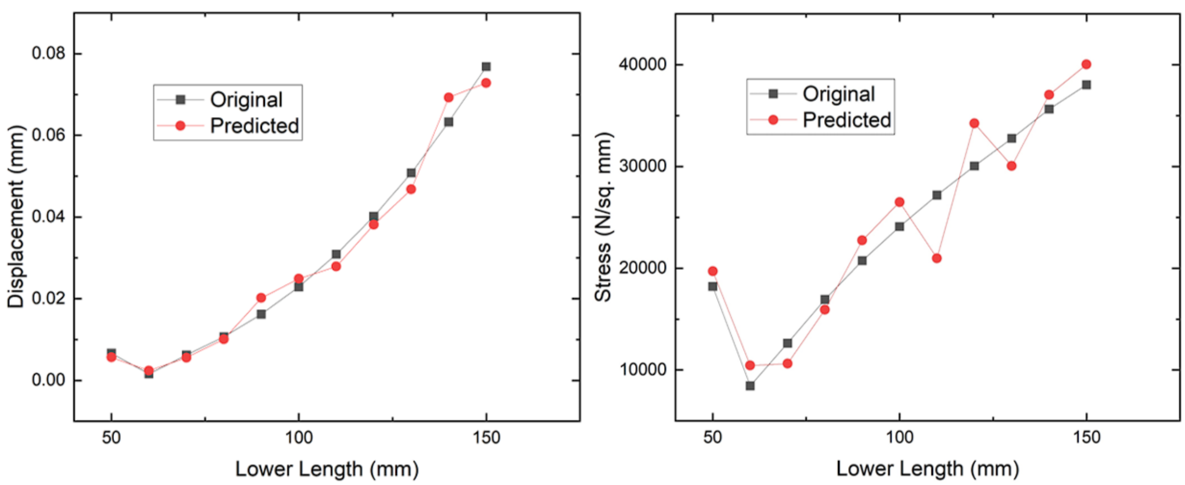


Figure 8: Displacement and Stress comparison between Original and Predicted values for ABS material keeping upper arm length constant at 50mm.

Conclusion

As the L-shaped bend suffer high mechanical stress and deformation due to high fluid momentum and in order to determine the FSI using ML model a database is required for the different model to learn and do the prediction without the further use of simulation. For achieving this goal, the KNN Regression model is selected because of its ability to predict multiple responses, in current case displacement and stress, while keeping the understanding and implementation of code as simple as possible. The FSI process and the algorithm for ML prediction is discussed earlier and a snapshot of the database (figure 6) is also provided. The KNN Regression model with 4 neighbours shows a very good fitness with the current database with training and testing R^2 Value of 0.9848 and 0.9769 respectively (table 3). And for the final evidence for the fitness of the model, figure 8 shows the comparison between original and predicted data for a section of ABS material with the fluid pressure distribution of inlet condition at 1m/s and it is observed that the ML model describes the original data nature quiet accurately.

References

[1]. Peskin CS. 1972 Flow patterns around heart valves: a numerical method. J. Comput. Phys. 10, 252 271. (doi:10.1016/0021- 9991(72)90065-4) https://doi.org/10.1016/0021-9991(72)90065-4

[2]. Peskin CS. 2002 The immersed boundary method. Acta Numer. 11, 479-517. https://doi.org/10.1017/S0962492902000077

[3]. Goldstein D, Handler R, Sirovich L. 1993 Modeling a no-slip flow boundary with an external force field. J. Comput. Phys. 105, 354-366. https://doi.org/10.1006/jcph.1993.1081

[4]. Saiki EM, Biringen S. 1996 Numerical simulation of a cylinder in uniform flow: application of a virtual boundary method. J. Comput. Phys. 123, 450-465. https://doi.org/10.1006/jcph.1996.0036

[5]. Mohd-Yusof J. 1997 Combined immersedboundary/B-spline methods for simulations of flow in complex geometries. Center Turbul. Res. Annu. Res. Briefs 161, 317-327.

[6]. Fogelson AL, Guy RD. 2008 Immersedboundary-type models of intravascular platelet aggregation. Comput. Methods Appl. Mech. Eng. 197, 2087-2104. https://doi.org/10.1016/j.cma.2007.06.030

[7]. Raymond JP. 2010 Feedback stabilization of a fluid-structure model. SIAM J. Control Optim. 48, 5398-5443. https://doi.org/10.1137/080744761

[8]. Faria CT, Inman DJ. 2014 Modeling energy transport in a cantilevered Euler-Bernoulli beam actively vibrating in Newtonian fluid. Mech. Syst. Signal Process. 45, 317-329. https://doi.org/10.1016/j.ymssp.2013.12.003

[9]. Pontaza JP, Menon RG. 2009 Prediction of VIV response of a flexible pipe by coupling a viscous flow solver and a beam finite element solver. In Int. Conf. on Offshore Mechanics and Arctic Engineering, ASME, Jan 1, vol. 43451. pp. 303- 309. https://doi.org/10.1115/OMAE2009-79150

[10]. Diop M, Mbaye I. 2017 Numerical method for unsteady fluid structure interaction problem. Appl. Math. Sci. 11, 1835-1844. https://doi.org/10.12988/ams.2017.75185

[11]. Long Z, Lu Y, Ma X, Dong B 2018 Pde-net. Learning pdes from data. In Int. Conf. on Machine Learning, PMLR, July 3, pp. 3208- 3216.

[12]. Long Z, Lu Y, Dong B. 2019 PDE-Net 2.0: learning PDEs from data with a numericsymbolic hybrid deep network. J. Comput. Phys. 399, 108925. https://doi.org/10.1016/j.jcp.2019.108925

[13]. Yu Y, Yao H, Liu Y. 2020 Structural dynamics simulation using a novel physics-guided machine learning method. Eng. Appl. Artif. Intell. 96, 103947. https://doi.org/10.1016/j.engappai.2020.103947

[14]. Shit S, Das D, Ezhov I, Paetzold JC, Sanches AF, Thuerey N, Menze BH. 2021 Velocity-to-pressure (V2P)-net: inferring relative pressures from time-varying 3D fluid flow velocities. In Int. Conf. on Information Processing in Medical Imaging, pp. 545-558. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-78191-0_42

[15]. Whisenant MJ, Ekici K. 2020 Galerkin-free technique for the reduced-order modeling of fluid-structure interaction via machine learning. In AIAA Scitech 2020 Forum Jan 5,1637. https://doi.org/10.2514/6.2020-1637