NEURAL NETWORK AND GENETIC PROGRAMMING IN PRESSURE LOSS ESTIMATION IN ECCENTRIC PIPE FLOW

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ABSTRACT

Studies of fluid flow in annular pipes have been popular in the petroleum engineering research. Most of the work has concentrated on CFD (Computational Fluid Dynamics) simulations, analytical and empirical models. In this study a neural network and evolutionary programming approach is developed to model the behavior of fluid flow in eccentric pipes. The model uses the fluid rheological parameters, density, mass flow rate, eccentricity, inner and outer pipe diameters, and predicts the pressure drop (ΔP) in the pipe in the flow direction. The evolutionary programming model uses basic mathematical operators, logarithm and sine functions. The results are compared with some experimental data obtained in literature and some Matlab CFD simulations. Preliminary studies indicate the neural network model performed better than the other models, evolutionary programming model can predict comparable pressure drop results, but not as effectively as the other models.

FLUID FLOW IN ANNULAR PIPES

Fluid flow through an annular space is a frequently encountered engineering problem in many disciplines including petroleum engineering, chemical engineering, food engineering, nuclear engineering, etc, that has been under investigation for many decades. If the annular space is concentric, the flow can currently be analyzed without much difficulty. However, if the annular space is eccentric, i.e., the axes of the inner and outer tubes do not coincide with each other, a great deal of effort is required. Unfortunately, the latter case represents the majority of the realistic situations. For example, in petroleum engineering, during drilling operations, the drillpipe is usually positioned eccentrically in the wellbore, especially in a deviated wellbore where drillpipe has a strong tendency to offset toward the low side because of the gravitational effects. In such cases, the frictional pressure drop inside the wellbore becomes different when compared with the concentric case. In Figure 1, the concentric and eccentric pipe configurations are shown.

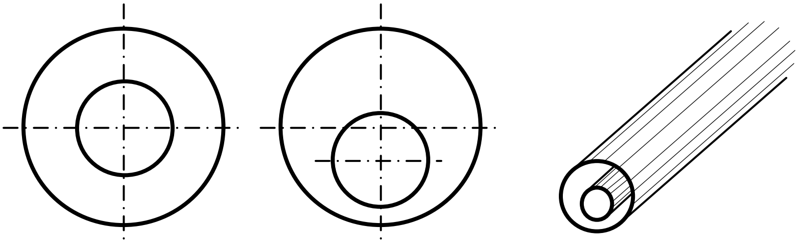

Figure 1: Left: Cross section of a concentric pipe configuration. Middle: Cross section of an eccentric pipe configuration. Right: 3-D view of an eccentric pipe configuration

Analytical and empricial techniques used for modeling the fluid flow in eccentric annular pipes exist in literature[2] using Newtonian and Non-Newtonian fluid types[5]. One of the subproblems in the fluid flow problem, especially in the oil industry is to estimate the pressure drop for non-newtonian fluids in eccentric annular pipes [6]. Newtonian fluids are studied extensively in the literature for such a problem and many experimental setups are developed, however non-newtonian fluid flow in eccentric pipes had lack of such interest, there has been theoretical studies, but experimental data for such problems are almost non-existent[4].

In general, the inner cylinder can be a rotating with respect to the outer cylinder[5], there has been studies modelling this behavior analytically [3]. In this study, as it is the preliminary stage, it is assumed that the inner and outer pipes do not have a rotational movement with respect to each other.

FLOW CONTROL PROBLEM

Flow control or CFD problems are generally characterized by solving the Navier-Stokes equations by finite element or difference methods. However not only this is a computationally intensive process, sometimes in certain cases, it might not be able to converge to an acceptable solution. In general methodology, simulation models are developed and used for solving CFD problems. The problem with the simulation technique is when the environmental parameters or states change, the simulation has to be recreated with the new parameters. This results in a problem if a real-time prediction model needs to be developed, since most simulation models can not address changes in the system settings and environmental parameters on the run.

Recently, other than the analytical and empirical models, more machine learning methodologies like genetic algorithms[8] and neural networks have started appearing in CFD applications [7][11]. Since neural networks have been used in many different applications where input-output relationships can not be easily defined by analytical methods[9], CFD can be considered one area that these techniques may provide better solutions than traditional techniques.

TESTS

In this study, three different techniques are used for estimating the pressure drop for non-newtonian fluids in eccentric annular pipes. The experimental data provided by Pereria et. al [1] is used in this study.

In the first model, a CFD simulation environment is created using the same parameters that are obtained from the experimental data. The flow in the simulations is governed by the Navier-Stokes equations

$$\rho\left(\frac{\partial u}{\partial t}(x,t)+(u\cdot\nabla u)(x,t)\right)=-\nabla p(x,t)+(\nabla\cdot\tau)(x,t)+F(x,t) \qquad (1)$$

where u is the velocity vector, p is the pressure, ρ is density, τ is the stress tensor, F is a body force, x is the spatial variable and t is the temporal variable. No-slip boundary conditions are assumed on the walls of the eccentric pipe, the inflow velocity is set based on the data provided in [1], and a Neumann-type constant pressure condition is assumed for the outflow. The specification of the initial and boundary conditions, as well as the execution of the CFD simulations were carried out on a solver based on Navier2d in Matlab [12], with custom extensions so as to accommodate the non-Newtonian flow at hand. Figure 2 shows a cross-section of the pressure distribution in the pipe for eccentricity 0.8 and an initial flow velocity of 0.609, where it can be seen that the pressure is highest on the left edge where the flow enters the pipe and it decreases with axial position, reaching its lowest value on the right edge. The difference between these two values is the pressure drop *ΔP*, which is the quantity to be estimated.

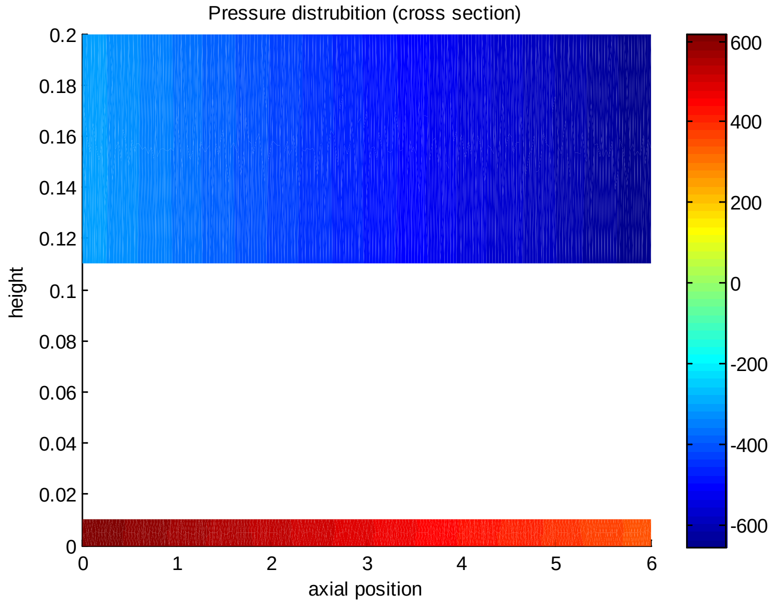

Figure 2: CFD simulation result showing a vertical cross section of the pressure distribution in the pipe for eccentricity 0.8 and initial flow velocity 0.609.

In the second model, a genetic programming approach is used and in the third model a neural network using the same parameters as inputs are created. All three models tried to predict the pressure drop at certain locations along the pipe.

The experimental data had the following parameters:

- Fluid viscosity (μ)
- Eccentricity (e)
- Initial flow velocity (v)
- Axial position (l)

Given these parameters all models tried to predict the pressure drop (ΔP) in the pipe. In the neural network model the backpropagation[10] model of 1 hidden layer with 4 hidden neurons is used. The learning was applied on the training data using the batch model with conjugate gradient technique. The training data and the cross validation data was obtained from the experimental data but chosen separately.

The tabulated experimental actual data used for testing is shown in Table 1.

Fluid type	Eccentricity	Initial flow velocity	Axial position	pressure drop
1	0.8	0.609	0.5	**75**
1	0.8	0.609	0.9	**110**
1	0.8	0.609	1.3	**134**
1	0.8	0.609	1.7	**166**
1	0.8	0.609	2.1	**187**
1	0.8	0.609	2.5	**212**
1	0.8	0.609	2.9	**232**
1	0.8	0.609	3.3	**253**
1	0.8	0.609	3.7	**277**
1	0.8	0.609	4.1	**297**
1	0.8	0.609	4.5	**318**
1	0.8	0.609	4.9	**338**
1	0.8	0.609	5.3	**358**
1	0.8	0.609	5.7	**378**
1	0.8	0.203	0.2	**10**
1	0.8	0.203	0.4	**15**
1	0.8	0.203	0.6	**25**
1	0.8	0.203	0.8	**30**
1	0.8	0.203	1.0	**35**
1	0.8	0.203	1.2	**40**
1	0.8	0.203	1.4	**45**
1	0.8	0.203	1.6	**55**
1	0.8	0.203	1.8	**60**
1	0.8	0.203	2.0	**65**
1	0.8	0.203	2.2	**70**
1	0.8	0.203	2.4	**75**

Table 1 Experimental Test data set

Comparison of the simulation model pressure drop estimation results and the neural network estimation results are tabulated in Table 2 with comparison with the actual experimental test results.

Experimental pressure drop	Simulation model estimation	Simulation difference	Neural Network estimation	NN difference
75	32.1849	42.81	71.42	3.58
110	56.0994	53.90	110.38	0.38
134	80.4055	53.59	139.46	5.46
166	102.4529	63.55	163.97	2.03
187	126.6191	60.38	187.30	0.30
212	148.9971	63.00	210.39	1.61
232	173.0547	58.95	233.01	1.01
253	196.5001	56.50	254.75	1.75
277	220.8541	56.85	275.53	1.47
297	246.0040	51.00	295.78	1.22
318	268.4337	49.57	316.16	1.84
338	292.1188	45.88	337.16	0.84
358	315.9865	42.01	358.30	0.30
378	339.1226	38.88	377.69	0.31

Table 2 Comparison of simulation and neural network models

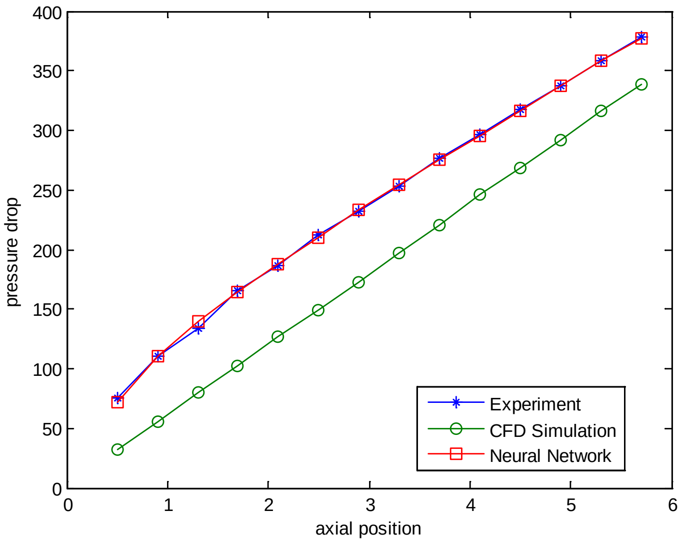

Figure 3: Comparison of experimental values of ΔP , with those obtained from the CFD simulation and neural network model.

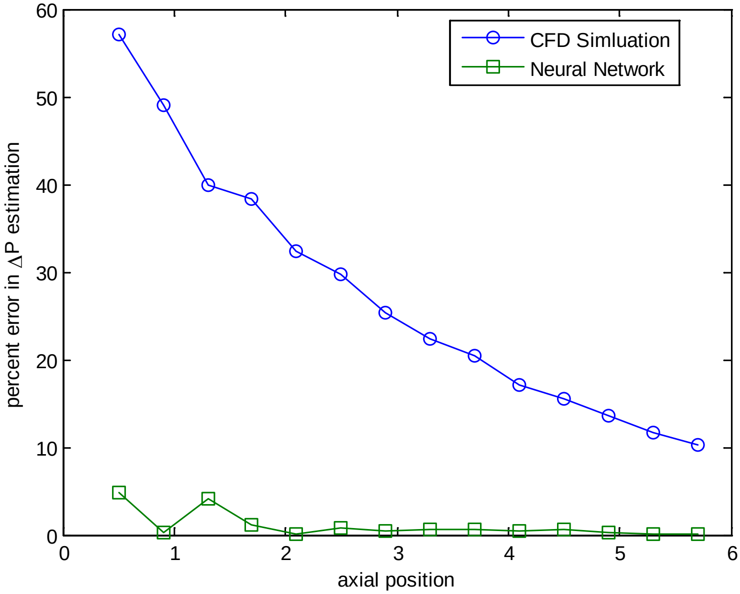

Figure 4: Percent error in estimating ΔP , for the CFD simulation and the neural network model.

Comparison of the simulation model pressure drop estimation results and the genetic programming estimation results are tabulated in Table 3 with comparison with the actual experimental test results.

Experimental pressure drop	Simulation model estimation	Simulation difference	Genetic Programming estimation	Genetic Programming difference
10	7.3373	2.66	5.03	4.97
15	13.1810	1.82	10.08	4.92
25	18.5477	6.45	15.16	9.84
30	24.1269	5.87	20.26	9.74
35	29.9056	5.09	25.37	9.63
40	36.0296	3.97	30.50	9.50
45	41.3272	3.67	35.64	9.36
55	46.9942	8.01	40.78	14.22
60	52.6634	7.34	45.93	14.07
65	58.1418	6.86	51.08	13.92
70	63.8695	6.13	56.23	13.77
75	69.3089	5.69	61.37	13.63

Table 3 Comparison of simulation and genetic programming models

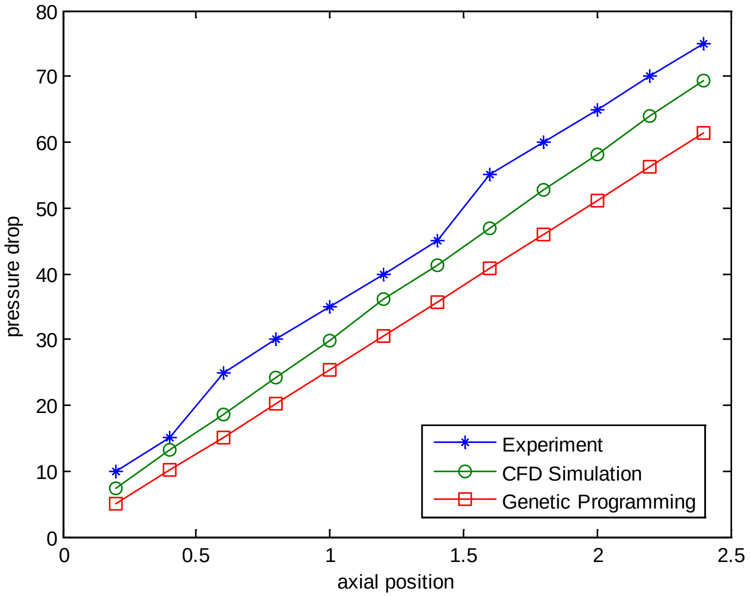

Figure 5: Comparison of experimental values of ΔP , with those obtained from the CFD simulation and genetic programming model.

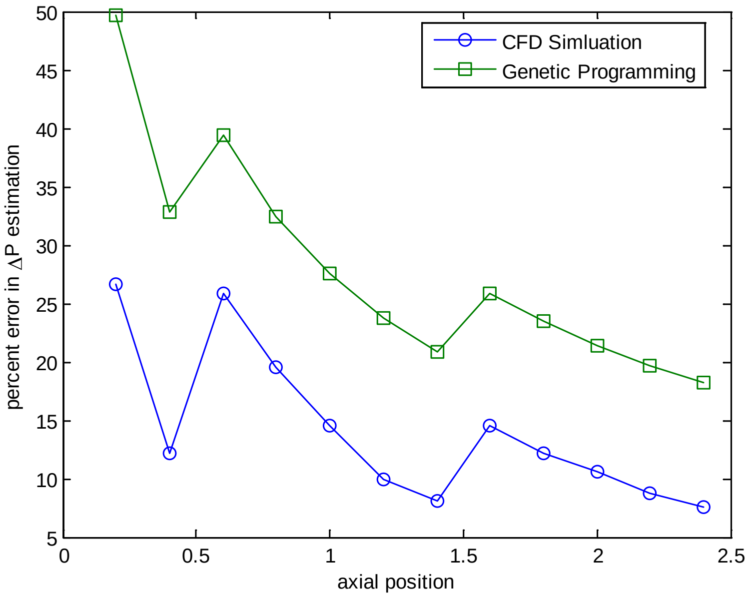

Figure 6: Percent error in estimating ΔP , for the CFD simulation and the genetic programming model.

RESULTS AND CONCLUSIONS

Two separate flow velocity was used in the tests, for the slower velocity case, simulation results were compared to genetic programming results and in the faster velocity case, neural network results were compared to simulation results.

When the results were analyzed, it was observed that the neural network model easily outperformed the simulation model when the fluid velocity was high. The simulation model however performed better than the GP model in the slower fluid velocity case, even though the difference in errors was not as significant as the former case. At this point more tests need to be done to see if there is a better GP model that can predict pressure loss better than the current configuration, GP model might not be suitable to these type of problems if additional results indicate similar outcomes.

These preliminary results indicate the neural network modeling of the pressure drop prediction in eccentric annular pipes can be a solution for real time estimation of this parameter. Since these are the initial results, more tests will be performed to verify that neural network can indeed be an answer to this computationally intensive problem.

There are ongoing tests for different parameter sets in order to implement the best model for pressure loss prediction. Furthermore, there is an effort to create a CFD and Fluid Flow Laboratory in the university in the near future. So it will be easier to obtain more experimental data. As a result, for future work, also inner cylinder rotation case will be considered and models for that problem will be developed.

NOMENCLATURE

CFD : Computational Fluid Dynamics
GP : Genetic programming
ΔP: Pressure Drop

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