OPTIMIZATION OF INTAKE MANIFOLD FLOW USING OPENFOAM BY GENETIC ALGORITHMS AND ARTIFICIAL NEURAL NETWORKS

MANIMARAN RENGANATHAN
Associate Professor, Thermal and Automotive Research Group, School of Mechanical and Building Sciences, University of Chennai Campus, Chennai, India 600127
Email: manimaran.nr@gmail.com

Keywords: *Intake manifold, Validation, Computational fluid dynamics, Genetic algorithm, Neural networks*

The increase in the performance of internal combustion engines for diesel engines continues to follow alternative ways in order to improve the flow characteristics, thereby improving the overall efficiency. This paper presents the computational fluid dynamics (CFD) modeling to study the effect of intake flow condition on the swirl ratio of a direct injection (DI) diesel engine. A single cylinder direct injection diesel engine with two directed intake ports whose outlet is tangential to the wall of the cylinder has been considered. The numerical results from this geometry are validated with the experimental results published in the literature. In order to enhance the swirl ratio, intake flow in different components are adjusted instead of modifying the intake manifold shape and profile. The experiments are designed by full factorial approach for 3 variables (three components of intake velocity) to study the in-cylinder turbulent flows in a computational way and accomplished using OpenFOAM software. The induced swirl and tumble at the end of compression stroke are also computed and visualized.
Numerous computations have been performed in this work during maximum intake valve lift and closed exhaust valve positions. To estimate the reliable data for predicted results, machine learning techniques such as artificial neural network is employed. Information is gathered for different combinations of intake velocity on swirl ratio. Genetic algorithm is applied to find the fittest data-set after several generations, thereby the best optimal flow components are determined. The results from design of experiments approach and neural network techniques are compared. The optimized model is found and results are verified with the validated CFD code.

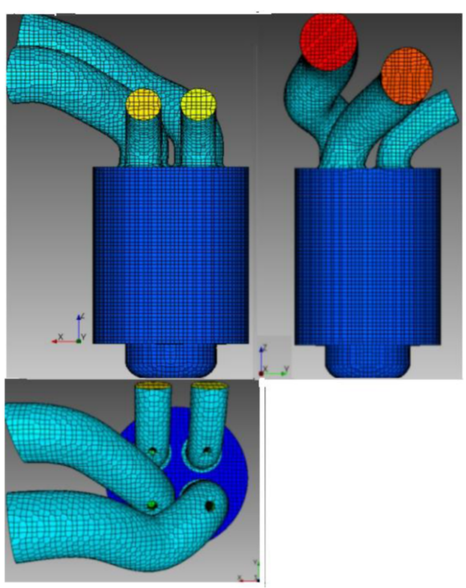

Figure 1: Meshed model of the single cylinder Diesel with dual intake ports.

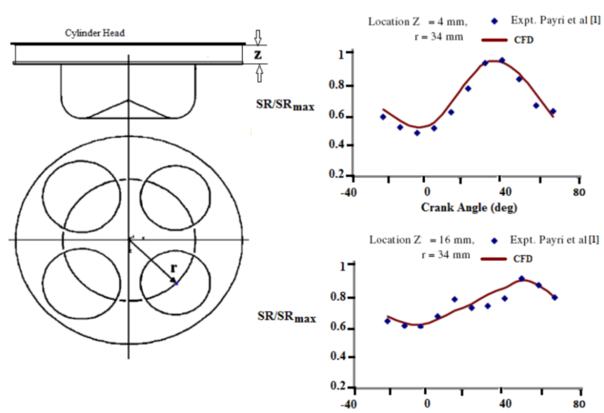

Figure 2: Validation of CFD with the engine experimental results of Payri et al [1].

A single cylinder DI diesel engine having a toroidal combustion chamber with two directed intake ports whose outlet is tangential to the wall of the cylinder and two exhaust ports has been used as shown in Fig. 1. The pre-processor snappyhexmesh is used to create the entire computational domain of the engine including intake and exhaust ports and open-source computational fluid dynamics code OpenFOAM [2] is used for the solution of governing equations and post

processing the results. The equations are solved in time according to the pressure-implicit-split operators (PISOfoam). The discretization of time derivatives is performed with a first order bounded implicit Euler method.
The computational mesh employed for the simulation is shown in Fig. 2. Hexahedral block structured mesh is employed for the entire computational domain with 505,542 cells (Fig. 1). Fig. 2 shows the variation of swirl ratio with crank angle near TDC position at two measuring locations after careful mesh and time independent studies. Decreasing trend in swirl ratio is observed during compression stroke due to friction at the wall. However, while approaching TDC, swirl is enhanced as the flow accelerates in preserving its angular momentum within the smaller diameter piston bowl. During the expansion stroke, reverse squish as the flow exits from the piston bowl and wall friction contributes to the sudden fall of the swirl ratio. The predicted results (Fig. 2) are generally in good agreement with experimental results at all locations.

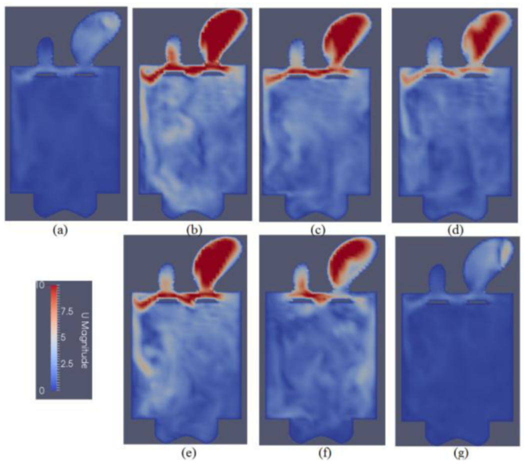

Figure 3: Velocity magnitude inside the section of cylinder for different cases.

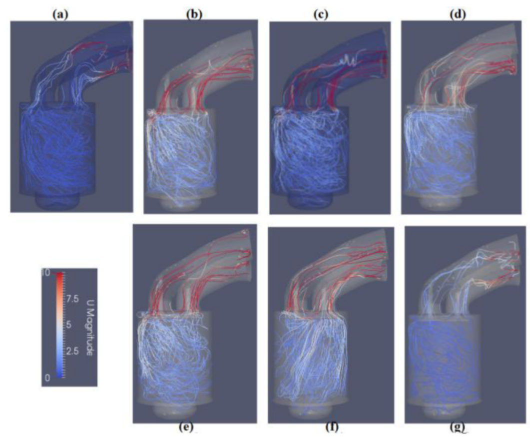

Figure 4: Stream lines inside the cylinder for different cases.

Fig. 3 and Fig. 4 which illustrate the variation of velocity magnitude and streamlines inside the cylinder for different cases. The cases are selected by varying the velocity components for air flow in the intake manifold while maintaining the identical mass flow rate in all cases. The results show faster decay of swirl during the expansion stroke at locations near the cylinder head due to reverse squishswirl interaction.
The optimization part by genetic algorithm followed in [3] is executed through a customized Python script. The predicted artificial neural network (ANN) model is used to find the objective function (the normalized swirl ratio). An ANN as followed in [4, 5, 6] is created and trained using the database results and tested for optimization during the looping inside the genetic algorithm. An optimal configuration is determined from this algorithm by allowing the populations to undergo generations with 5% mutation, such that the fittest data converges to an optimum. The CFD study for the optimized configuration is carried out and normalized swirl ratio is evaluated. It is found that the normalized swirl ratio coefficient values are found to be 0.745 and 0.76 from ANN and CFD codes respectively. This is observed in the proposed model with an improved velocity field. The flow components are changed but the mass flow rate is maintained constant, yielding an improved swirl ratio.

References

[1] F. Payri, M. J. Desantes, and V. J. Pastor, "Ldv measurements of the flow inside the combustion chamber of a 4-valve d.i. diesel engine with axisymmetric piston-bowls," *Experiments in Fluids*, vol. 22, no. 2, pp. 118–128, 1996.

[2] "Openfoam User Guide 2.3.1," 2007. [Online]. Available: http://www.openfoam.org

[3] S. K. R. Dwarshala, P. Ramadandi, R. Shaik, and R. Shankar, "Practical considerations in the airflow optimization of a single cylinder diesel engine," *SAE Technical Paper 2014-01-1705*, 2014.

[4] S. M. Aceves, D. L. Flowers, J. Chen, and A. Babajimopoulos, "Fast prediction of hcci combustion with an artificial neural network linked to a fluid mechanics code," *SAE Technical Paper 2006-01-3298*, 2006.

[5] G. W. Malaczynski, M. Mueller, J. Pfeiffer, D. Cabush, and K. Hoyer, "Replacing volumetric efficiency calibration lookup tables with artificial neural network-based algorithm for variable valve actuation," *SAE Technical Paper 2010-01-0158*, 2010.

[6] Y. Sun, T. Wang, Z. Lu, , L. Cui, and M. Jia, "The optimization of intake port using genetic algorithm and artificial neural network for gasoline engines," *SAE Technical Paper 2015-01-1353*, 2015.