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Numerical Study of Intake Flow Optimization using Genetic Algorithm and Artificial Neural Networks

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EXTENDED ABSTRACT

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it. The increase in the performance of internal combustion engines for diesel engines has driven to follow alternative ways in order to improve the flow characteristics. This paper presents the computational fluid dynamics (CFD) modeling to study the effect of intake flow condition on the swirl ratio and volumetirc efficiency 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 and 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 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 and volumetric efficiency. Genetic algorithm is applied to find the fittest data-set for several generations thereby the best optimal flow components are determined. The results from design of experiments approach and neural network techniques are compared.

A. Introduction

The intake port design study has come from various studies including the flow visualization using a flat glass plate to the full end CFD codes for entire analyses. Payri et al (1996) measured the ensemble averaged tangential and radial velocity components and turbulence intensity to investigate the flow patterns inside a four valve single cylinder motored diesel engine using LDV, for various engine speeds, swirl numbers and piston bowl geometries, under conditions similar to those of a production engine. Karen et al (2004) made the in-cylinder flow and steady flow measurements using three different intake port geometries at three different port orientations. Instantaneous realizations of the flow field showed that the flow exhibited significant cycle-to-cycle variation.

Artificial Neural Networks are studied for better prediction with the actual and the experimental results. Bin Wu et al (2004) proposed using an artificial neural network to estimate the air flow rate in a VVT engine. Trained with steady-state dynamometer test data, the ANN model represents the air flow rate as a function of four independent variables. Adrian et al (2006) predicted the flow physics by the numerical simulation for the intake valve region and showed that the intake port curvature has a great impact on the flow development in the valve gap. The computational simulations show that as the flow is accelerated near the convex wall and decelerated along the concave side of the intake port. Gerard et al (2010) presented an ANN approach to real-time volumetric efficiency modeling of an engine with many degrees of freedom. This is considered important since the traditional methods, as opposed to the ANN approach, are reaching their limit of being able to scale up with the additional degrees of freedom introduced by current and future engine optimization. Yanzhe et al (2015) carried out using a GA-ANN procedure for automatically optimizing the structure of a tangential port for different requirements of flow motion in gasoline engines.

From the literature obtained till date, it is observed that many studies have been conducted on intake geometry optimization of a single cylinder gasoline engine. It can be found that intake flow components in a three-dimensional flow also play a vital role in tumble and swirl motions. The influence of flow velocity components in intake port flow is an interesting investigation and followed in this study. Single objective optimization on finding the optimized parameters of the velocity components angles to improve the swirl ratio constitutes the core of the present work. ANN and CFD tools are used to find solution to the problem as they are found and proven to be efficient in getting a quick solution. Genetic Algorithm is used for optimization, whereas back propagation algorithm is followed in the ANN technique. CFD simulations are carried out at different combinations of intake flow components using PISO algorithm in an open-source software.

B. Methodology

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. The geometrical details of the engine are summarized in Table 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 is used for the solution of governing equations and post processing the results. The computational mesh employed for the simulation is shown in Fig. 1. Hexahedral block structured mesh is employed for the entire computational domain with 505,542 cells (Fig. 2). The subject for this study is to improve the swirl ratio in a 4-stroke, single cylinder, twin-intake diesel engine.

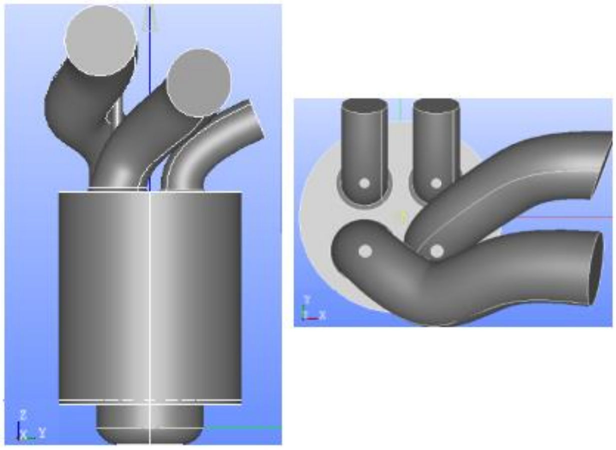

Figure 1.Geometrical model of the single cylinder Diesel engine with dual intake ports.

Figure 1 shows the side, top, and rear views of the baseline model. The cylinder bore, stroke length and other details are shown in Table 2. Also shown in Fig. 1 is the origin of the coordinate system used. Numerous CFD simulations are carried out for different intake flow velocities, varying u_x,u_y and u_z to obtain the best swirl ratio but maintaining the identical mass flow rate at intake. The data for the swirl ratio thus obtained is stored in a database for ANN prediction. Once the data is trained in an ANN, the optimized swirl ratio is obtained using the Genetic algorithm.

Swirl Ratio : $U_{Ang}/(2\Pi N/60)$ (EQN 1)

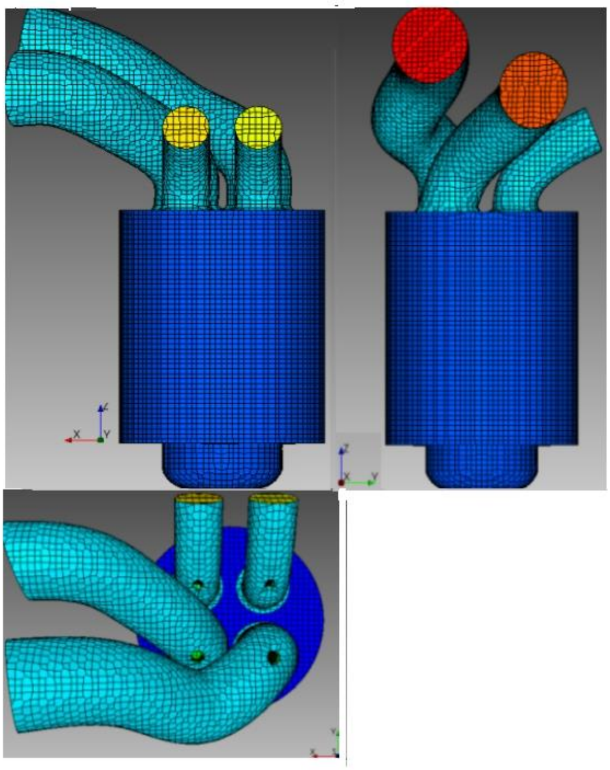

Figure 2.Meshed model of the single cylinder Diesel engine with dual intake ports.

An artificial neural network (ANN) was chosen as the solver approximation method. A solver approximation method is used to create an approximate relationship between the design parameters and response behavior, in this case the behavior of swirl ratio. Genetic algorithm has the ability to explore and exploit simultaneously, a growing amount of theoretical justification, and successful application to real-world problems. In statistics, fractional factorial designs are experimental designs consisting of a carefully chosen subset (fraction) of the experimental runs of a full factorial design

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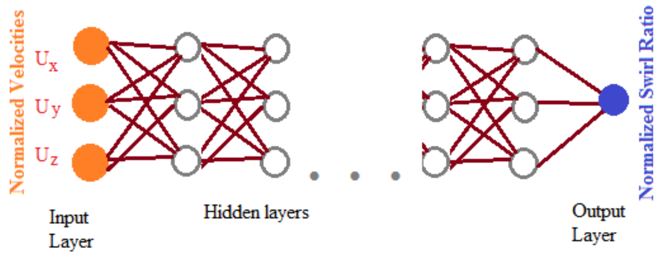

Figure 3.ANN model used in the present study

TABLE 1. ENGINE SPECIFICATIONS

Bore, Stroke	13,15 cm
Displacement	1991 cc
Rated speed	2000 rpm
Bowl diameter, depth	76, 29 mm
Compression ratio	15.5:1
Intake valve diameter	44.4 mm
Intake valve opening	9 deg bTDC
Intake valve closure	62 deg aBDC
Exhaust valve opening	43deg bBDC
Exhaust valve closure	10 deg aTDC

C. Results and Discussions

The CFD calculations are performed to validate the base case with the experimental data published by Payri et al (1996). Fig. 4 shows the variation of swirl ratio with crank angle near TDC position at two measuring locations. 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 are generally in good agreement with experimental results at all locations. Further the datasets for ANN calculations are carried out with the batch processing of CFD calculations for the trained data shown in appendix A. Some of the cases from the trained data are shown in Fig.5 and Fig. 6 which illustrate the streamlines and variation of velocity magnitude inside the cylinder. The results show faster decay of swirl during the expansion stroke at locations near the cylinder head due to reverse squish–swirl interaction.

Validation of CFD study

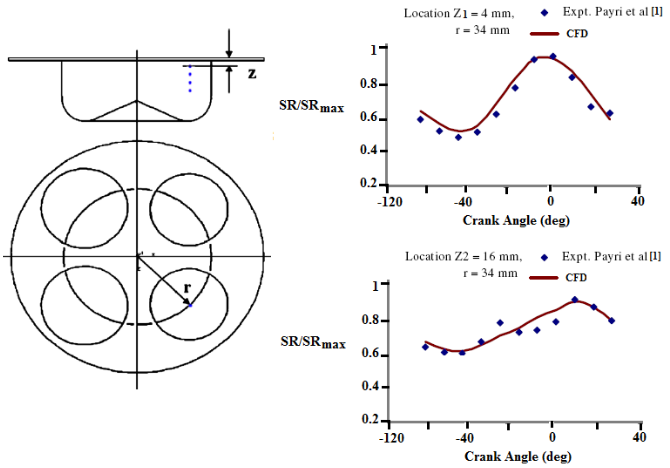

Figure 4.Validation of CFD with the experimental results of Payri et al (1996)

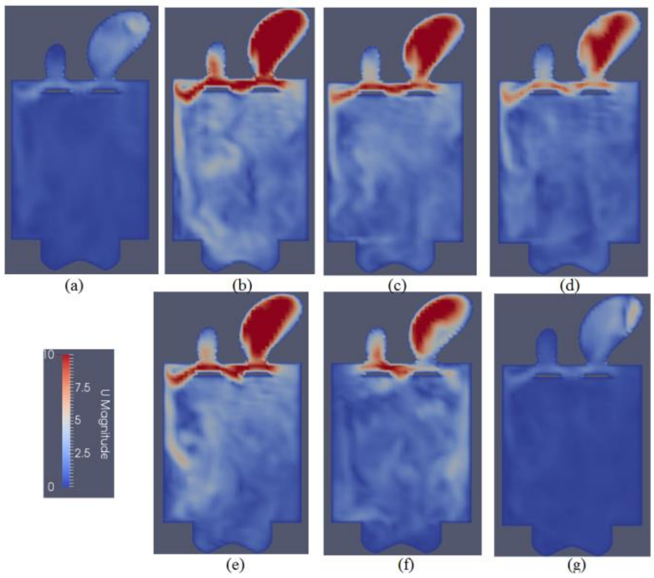

Figure 5.Velocity magnitude inside the section of cylinder for different cases

ANN- Training, Testing and Validation

The database is trained (27 elements) and tested (25 elements) in order to determine the sensitiveness of the prediction error during the optimization study. These data are shown in appendix for reference. Exponential sigmoid function is used in this study for prediction. To avoid over-training, regularization allows the use of all samples for training, and for relatively small databases regularization yields better generalization. The normalized swirl ratio values are predicted for every test case and the response curves are plotted.

Exponential Sigmoid Function $f(Z) = 1/(1 + e^{-z})$ (EQN 2)

The difference in the output values between testing and training sets are found and plotted in Fig. 7. The performance of the neural network model for the prediction of normalized swirl ratio is shown in Fig. 8. The response surface is obtained for the testing data and shown in Fig. 8. From the ANN study, it is understood that the response varies from 0.740 to 0.754. The results from the ANN and the CFD amounts to an average error of -2.49 %. Deviations between experimental data and ANN data in both testing and training are very small and negligible. There is a good agreement between the ANN model calculation and CFD simulation results. From the ANN and DOE studies, one can arrive at a possible conclusion that individual velocity components promote an increase in swirl ratio. Fig. 9 shows the output from the DOE study by using the fractional factorial approach for two factors. DOE results indicate the maximum of any velocity component leads to increase in swirl ratio.

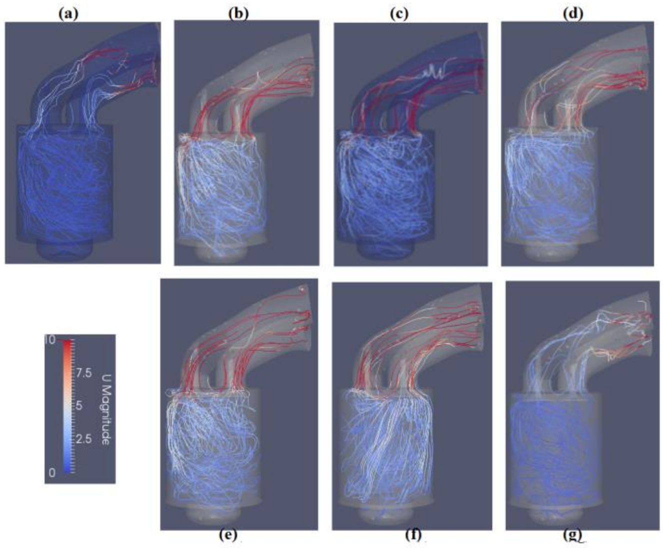

Figure 6.Stream lines inside the cylinder for cases (a) – (g)

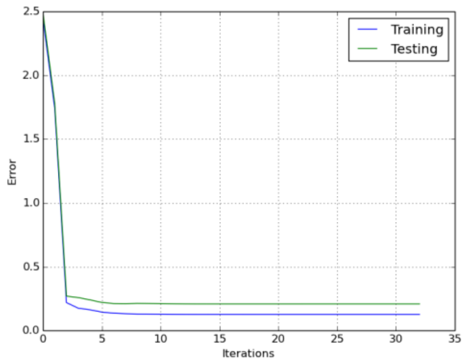

Figure 7.Difference between the trained and tested data

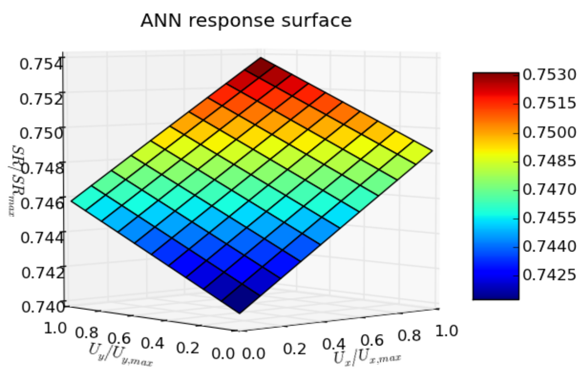

Figure 8.Response from tested data of ANN after training

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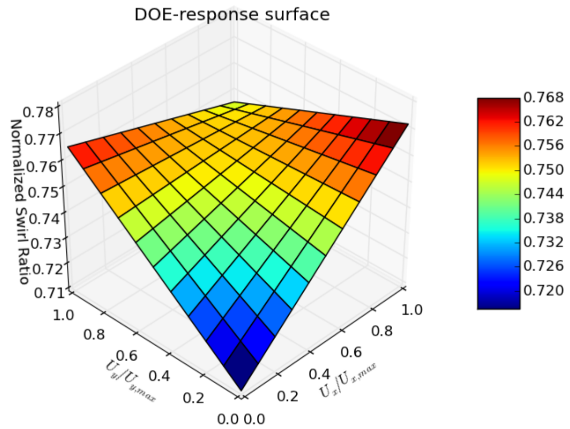

Figure 9.Response surface generated from design of experiments using fractional factorial approach

Optimization using GA code

The optimization part is executed through a custom Python script called Genetic Algorithm code. The predicted ANN model is used to find the objective function (normalized swirl ratio The specifications about the algorithm is shown in Table 2. The python script houses the ANN code, whose trained output function is used for evaluating the objective function in the genetic algorithm code. The output from the code evaluation is shown in Fig. 10. The variables start at a random value in the given range and oscillate towards finding the optimum while undergoing the iteration loop in the algorithm to find the maximum normalized swirl ratio. A CFD simulation is carried out to verify the optimal GA.

TABLE 2. GA-CODE SPECIFICATIONS

Coding Method	Real
Size of population	52
Crossover method	single point (half width)
Probability of cross-over	0.5
Mutation method	single point
Probability of Mutation	0.05
Selection	Tournament

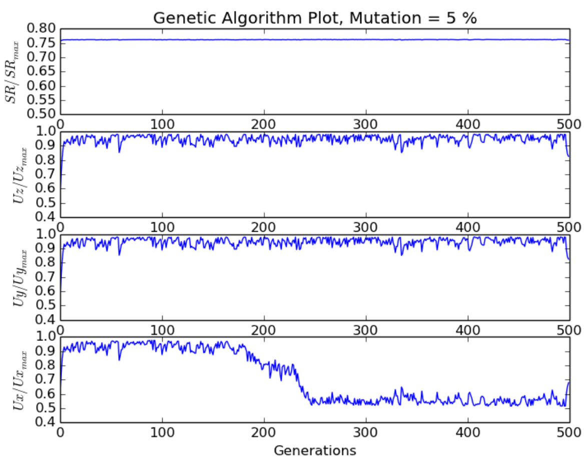

Figure 10. Solution output from optimization using GA python code

The CFD study for the optimized configuration is carried out and normalized swirl ratio is evaluated. It is found that the normalized SR coefficient values are found to be 0.745 and 0.76from ANN and CFD codes. This is observed in Fig. 11 with an improved velocity field from the case (g). The flow components are changed but the mass flow rate is maintained constant, yielding an improved SR.

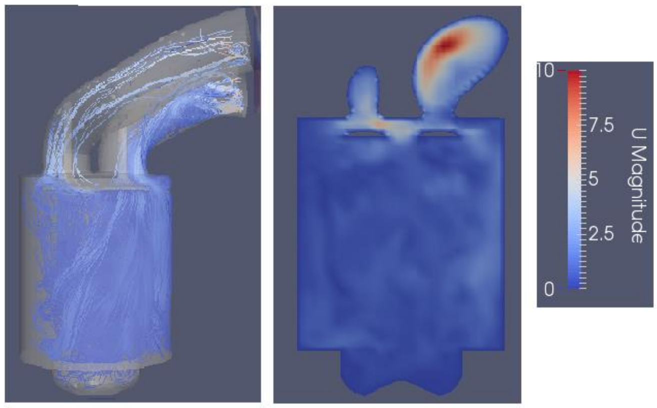

Figure 11. Stream lines and velocity magnitude in the cylinder for optimized flow components

D. Conclusions

A quick procedure for optimization of an intake physical flow process with respect to swirl ratio has been developed and investigated. The optimization method employs the genetic algorithm coupled with DOE and ANN responses from respective studies. The swirl ratio increases effectively by using the coupled CFD-ANN-GA optimization codes. The normalized swirl ratio is found to increase from 0.64 to 0.76. This results in the change in flow field, towards increasing the tendency of swirl ratio. The future work includes the quality and size of the database of GA, DoE and ANN.

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