Machine learning based blade design optimisation of the NeoVAD

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Introduction

The NeoVAD is a proposed paediatric axial-flow Left Ventricular Assist Device (LVAD), small enough to be implanted in infants. The design of the impeller and diffuser blades is important for hydrodynamic performance and hemocompatibility of the pump. This study aims to implement blade optimisation utilising Computational Fluid Dynamics (CFD) modelling, machine learning and global optimisation techniques.

Steady state fluid simulations of 32 base designs were carried out using ANSYS CFX. For each of the 32 pump base-designs, a range of mass flow rate conditions were simulated, using the Shear Stress Transport (SST) RANS turbulence model, to give a view of the pressure-flow curve.

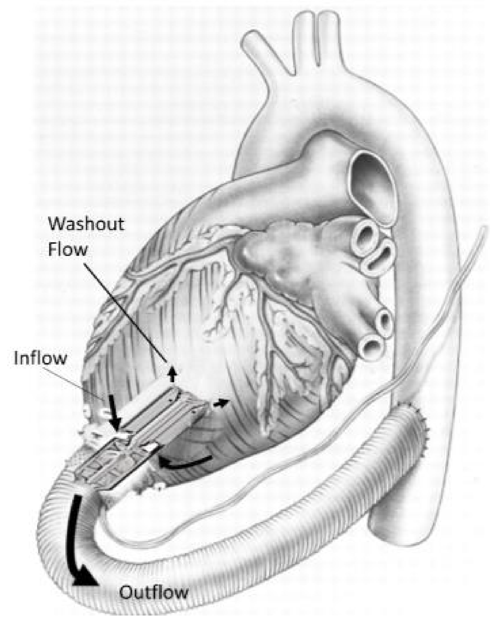


Figure: Location of NeoVAD in the heart

Machine learning aided optimisation

As fluid simulations are computationally expensive, a surrogate model was required to allow the optimisation routine to conduct an efficient search; a Bayesian Regularized Artificial Neural Network (BRANN) predicted the optimisation objective at design points not explicitly simulated. A genetic algorithm utilised the surrogate model to optimse the design for two sperate objective functions: maximum pressure head at 2 litres/min, 20'000 rpm; and maximum efficiency at a design point of 70 mmHg, 2 litres/min.

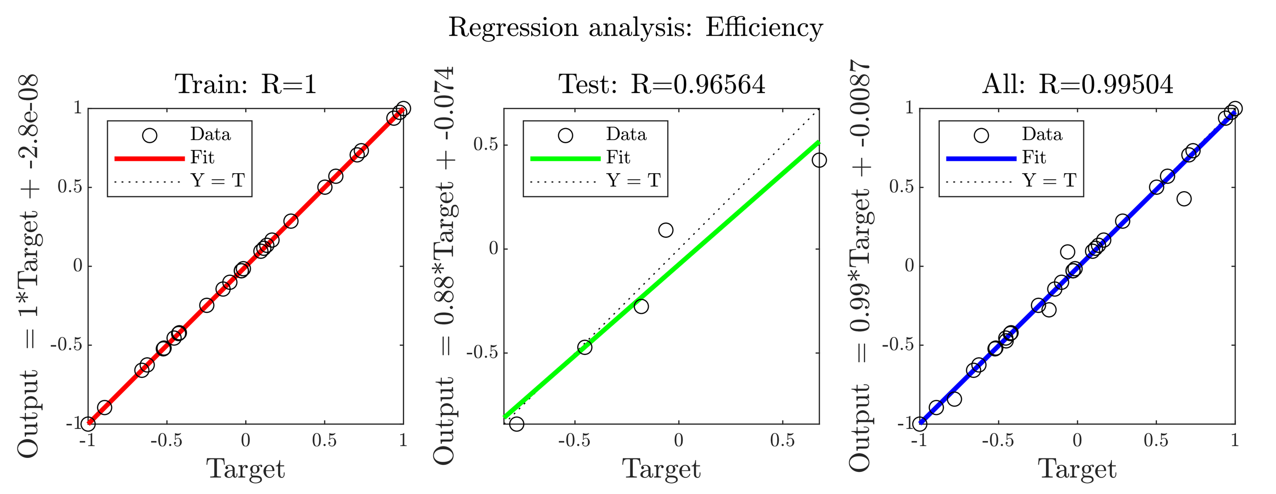


Figure: Regression analysis for BRANN trained to predict pump efficiency showing training set, test set and all data points.

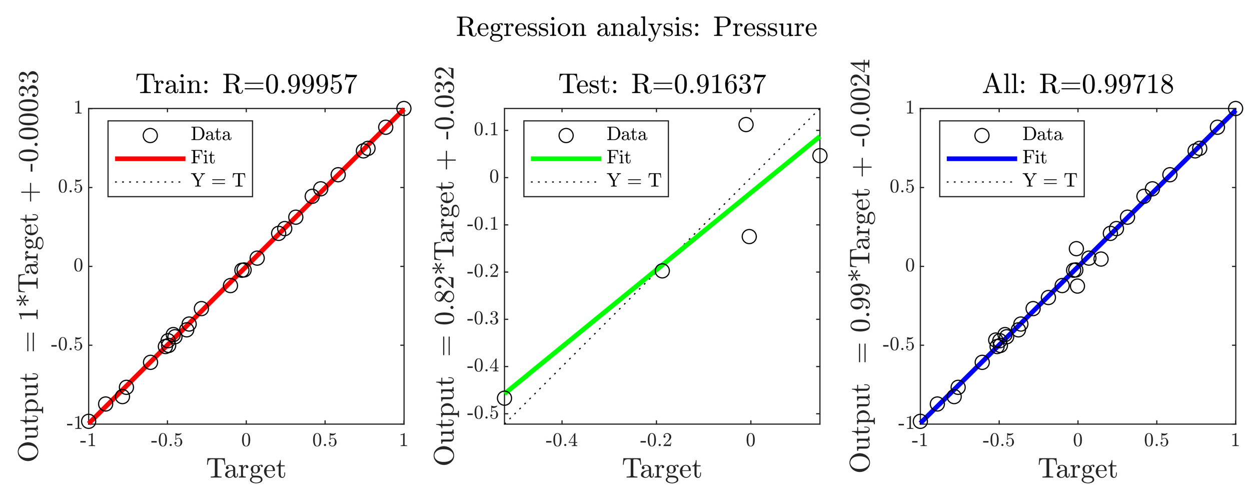


Figure: Regression analysis for BRANN trained to predict pump pressure head showing training set, test set and all data points.

Geometry

Circular arc impeller and diffuser blades of constant thickness were parameterised with five variable parameters: impeller chord length, inlet and outlet angle C_{imp}, β_1, β_2; diffuser chord length and inlet angle C_{diff}, α_2.

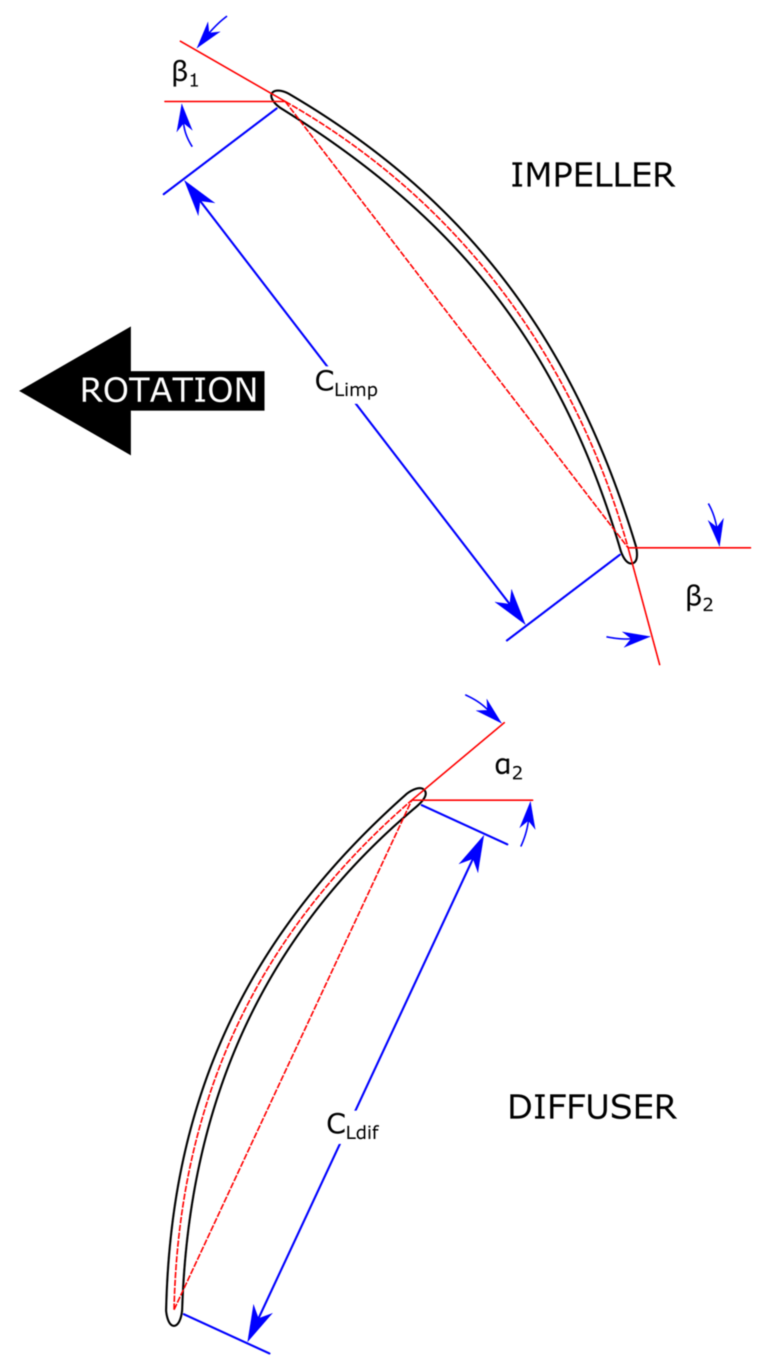
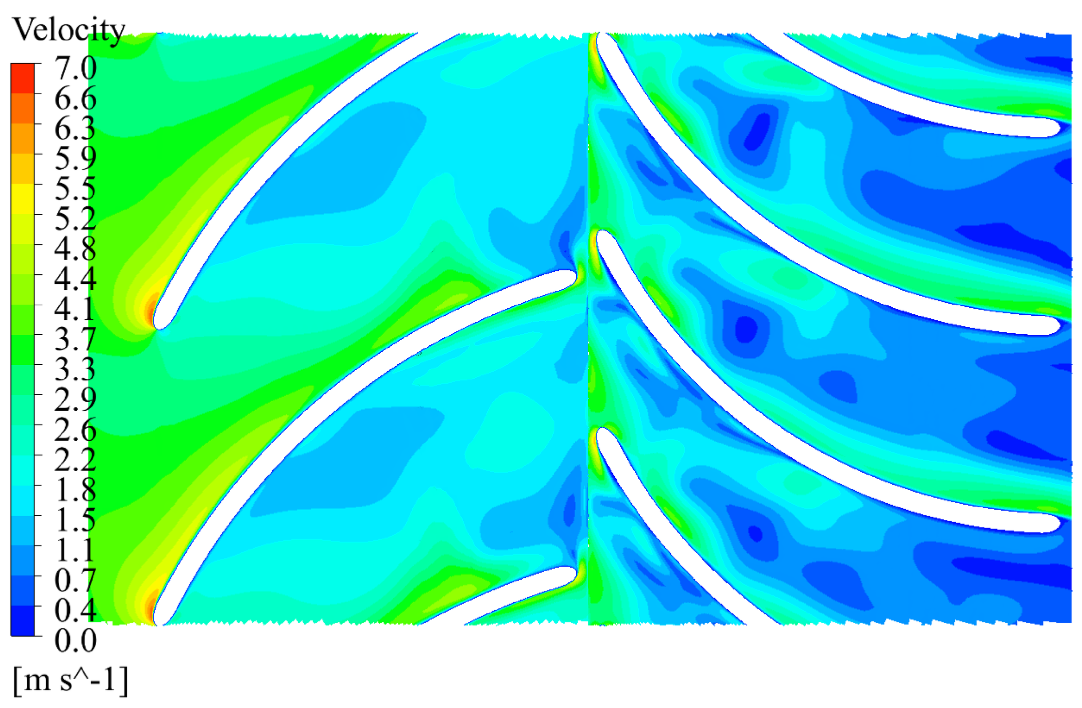
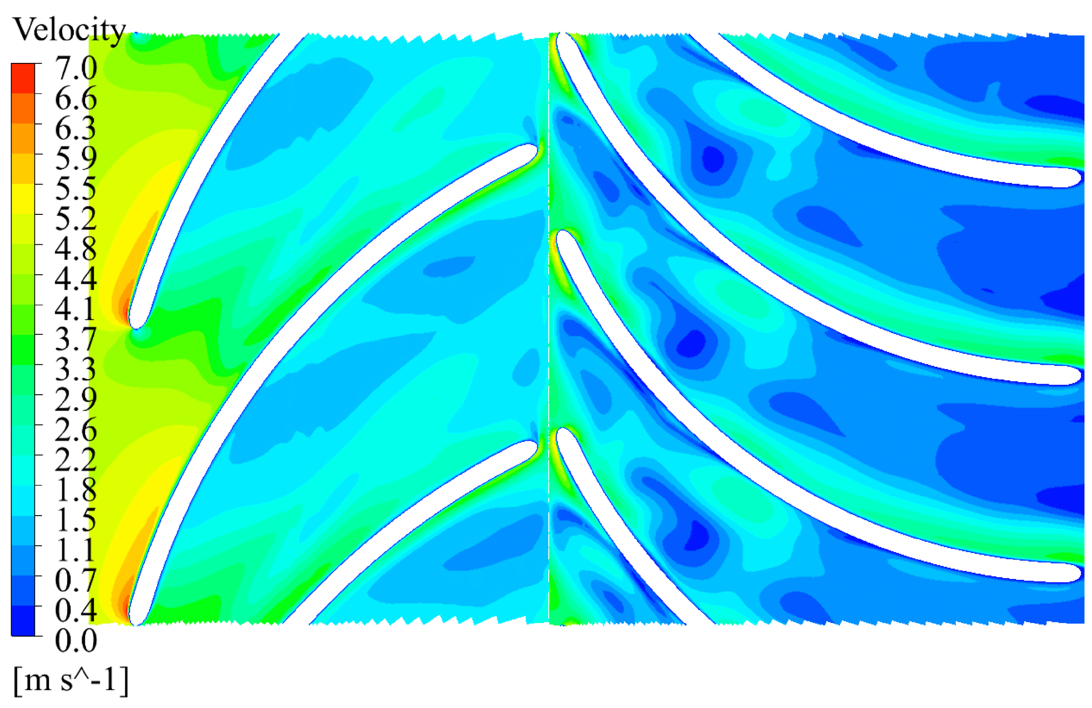


Figure: Axial pump schematic showing all five design parameters

Results



(a) Geometry and velocity contours at a 2D slice at mid-span for previously best performing pump



(b) Geometry and velocity contours at a 2D slice at mid-span for newly optimised pump

Figure: Results of the Artificial Neural Network enabled Genetic Algorithm optimisation of NeoVad blade designs, showing geometry of the previously best performing pump and a newly designed optimised pump.

Two objective functions were considered as analogues to hydrodynamic performance and haemocompatibility: respectively, maximising pressure head at constant rotating speed, = 20000 rpm, and maximising efficiency at a design point of pressure head, H = 70 mmHg, and flow rate, Q = 2 L/min. Both constrained optimisation routines converged upon the same design, which offered a 11.3 mmHg increase at 20000 rpm (an 8.8% performance increase) and a 4.2% increase in efficiency at design point (a 16.6% performance increase) as compared to the best performing pump from the 32 base designs

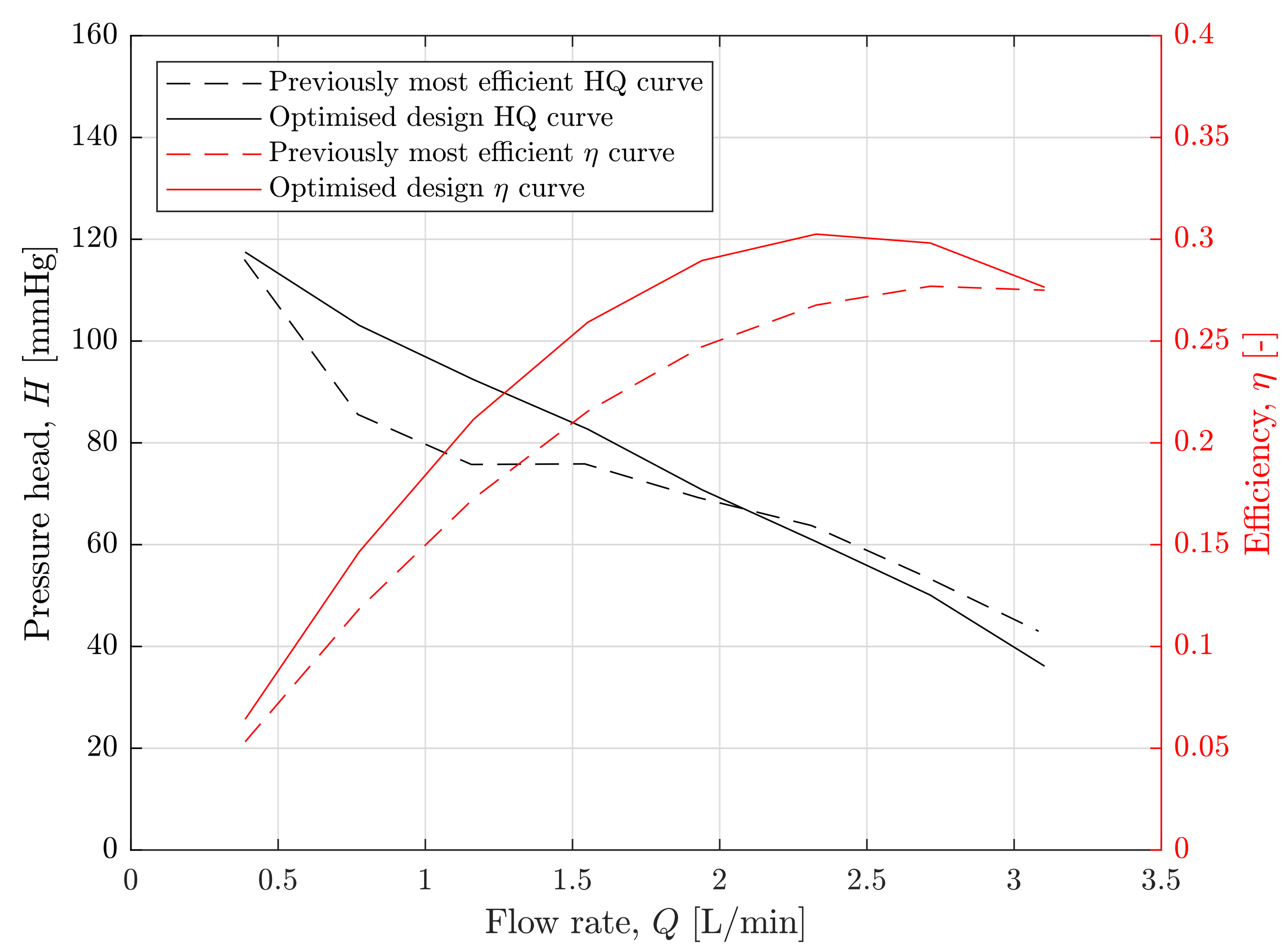


Figure: Comparison of pressure head vs. flow rate HQ curve and efficiency curves, showing increase in efficiency at the design point of $Q = 2$ L/min, $H = 70$ mmHg.

Conclusions

An optimisation method for the blade design of LVADs has been shown to work for a single objective function. The simulations that form the basis of the surrogate model, however, must be revisited to ensure better agreement with experimental data and be extended to fully transient in future optimisations. A larger and wider ranging data-set and a multi-objective optimisation routine are the next step in this research.

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