PRE-CONDITIONING OF TRAINING DATA FOR GAUSSIAN PROCESS REGRESSION ENABLED OPTIMISATION OF THE NEOVAD

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Introduction

The NeoVAD is a proposed axial Left Ventricular Assist Device (LVAD) specifically designed for use in paediatric patients between 5 and 20 kg. Paediatric patients often receive LVADs designed for adults that are operating externally and off-design due to the incompatible size of these devices [1,2]. The NeoVAD will be the first fully implantable LVAD for patients in this range, greatly increasing the quality of life by reducing the risk of infection and by ensuring device compatibility with small children.

To greatly reduce the computational expense of the blade design process, machine learning enabled surrogate models are created from a series of computational fluid dynamics (CFD) simulations that allow an optimisation routine to find the optimal design without the need for any additional simulations [3]. When creating the surrogate models from limited training data, care must be taken to ensure that the data are well conditioned to create reliable surrogate models.

Methods

The NeoVAD pump is an axial single-stage design consisting of a 2-blade rotor and a 3-blade stator. The blades are circular arc shaped, with constant thickness. The blades are parameterised using the following parameters: rotor inlet angle, β_1, rotor outlet angle, β_2, stator inlet angle, α_2, rotor chord length, C_{rot}, and stator chord length, C_{stat}. A base set of 32 designs were created and were subsequently simulated using *Ansys Academic Research CFX, Release 21.1 (Ansys Inc.)*. Optimising for either maximum efficiency or minimum dissipated energy at a chosen operating point should yield the same design as they are related by the equation

$$e_{loss} = \Delta P\left({}^{1}/_{\eta} - 1\right)$$

where, e_{loss} denotes dissipated energy, ΔP pressure increase over the pump, and η efficiency. To examine the effect of the spread of data on surrogate model accuracy Gaussian Process Regression was used to fit to calculated efficiency, η, dissipated energy, e_{loss}, and by using a Box-Cox power transform of both efficiency and dissipated energy data.

Results

The spread of data is visualised in Figure 1. The Kolmogorov-Smirnov test was used to compare the normality of data and p-values were 0.82, 0.87, 0.94 and 0.91 for efficiency, dissipated energy, Box-Cox efficiency, and Box-Cox dissipated energy, respectively. The resulting optimal designs were compared between all four surrogate model creation methods and can be seen in Table 1.

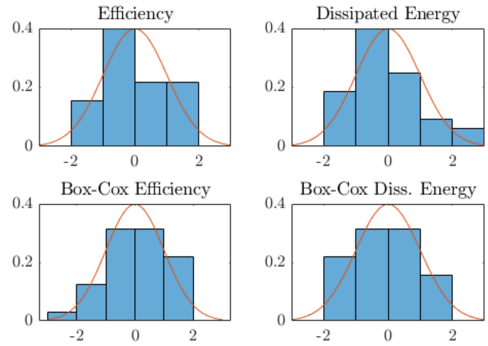

Figure 1: Normalised histograms of data over the 32 base designs for Efficiency, Dissipated Energy, Inverse Dissipated Energy and Box-Cox Transform Dissipated Energy.

	β_1 [°]	β_2 [°]	α_2 [°]	C_{rot} [mm]	C_{stat} [mm]	η [-]	e_{loss} [J/L]
η	10.0	60.0	32.2	15.6	14.7	0.35	17.3
e_{loss}	10.0	60.0	29.6	16.3	10.5	0.50	9.3
BC η	10.0	60.0	31.3	16.4	13.4	0.40	13.8
BC e_{loss}	10.0	60.0	31.9	16.2	14.2	0.37	15.4
Mean	10.0	60.0	31.3	16.1	13.2	0.41	14.0

Table 1: Design parameter results and surrogate predictions for each of the four surrogate models and the mean values across designs. Parameters in green indicates closest to mean and in red indicates furthest from mean.

Discussion

The resulting designs seen in Table 2 are sensitive to the spread of the training data. The rotor design is robust, in part to the constraints being set on allowable angles but also showing a maximum deviation of only 3% from the mean value. The stator design is much more sensitive showing a maximum deviation of 7% from mean in outlet angle and 20% deviation in chord length. Examining which designs deviate the most and least suggests that training data with a more Gaussian-like distribution results in more reliable surrogate models.

References

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