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OPTIMIZATION OF SMALL-SCALE HYDRAULIC STRUCTURES FOR POWERED EXOSKELETONS

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ABSTRACT

Generative design is an optimization process that is well-suited for various applications in fluid power, including untethered assistive technology exoskeletons powered through hydraulics. While generative design is capable of improving factors such as efficiency, system weight, and surface temperatures, there are currently no solutions that can address these factors simultaneously. The long-range goal of this research is to develop a multiphysics generative design process that combines solid mechanics, fluid mechanics, and heat transfer into a single algorithm to produce designs for high-pressure hydraulic systems that also provide structural support against external loads and passive cooling all in a single integrated structure. To create a generative design algorithm, a Python pipeline was constructed to interface with existing software applications to iterate through geometry creation, meshing, finite volume method, and sensitivity analysis. The pipeline was validated using a simplified case study of pressurized fluid flow through a pipe with a 90-degree bend where the flow path was modified between a fixed inlet and outlet to reduce pressure drop by 37.2±0.4%, corresponding directly to a reduction in battery size and, therefore, system weight. Future work will use multiphysics sensitivity analysis and machine learning to inform the iterative geometry refinement.

Keywords: Generative design; computer-aided engineering; hydraulic; optimization; design; medical and bio-design of mechanics and robotics; mobile robots; robot design; sensitivity analysis for design; simulation-based design

1. INTRODUCTION

Hydraulics is a good choice for power transmission due to its high force, high power density, stiffness, and ability to deliver power through flexible hoses [1]. Small-scale hydraulic power has applications in wearable exoskeletons and mobile robotics; however, scale reduction introduces significant issues in efficiency, thermal management, and system weight [1]. A robotic exoskeleton is defined by its portability and ability to interface with the user. In meeting these requirements, it must conform to the human body, be unobtrusive, and have a low system weight [7]. Several existing design optimization tools address these concerns.

Computation-based optimization can be classified as topology, size, topometry, shape, topography, or freeform [2] [3] [4] [5] [6]. The general approach of each type of optimization is to evaluate a design based upon one or more goals, such as reducing mass or temperature and then make an informed geometric change to improve performance over the previous design iteration. What differentiates each type of optimization is the level of freedom offered to make changes. For example, shape optimization methods are restricted to a shape, such as a tube, and can only change parameters such as length or curvature but cannot puncture the tube or change the surface texture. In contrast, the topology optimization method allows every element of a geometry to be movable or removable [7]. Optimization has led to significant improvements to designs based on structural mechanics, fluid mechanics, and heat transfer [8] [9] [10].

This paper presents the initial phases of a computational pipeline that brings together several applications for iterative generation, evaluation, and modification of a design until an optimum is reached. The pipeline is validated with a case study involving simple pipe flow with a 90-degree bend. This study demonstrates the feasibility of the pipeline to be used for generative design for a wide range of applications. The long-term goal of this work is to provide new design tools and new design guidelines for the creation of small-scale hydraulic systems that must meet stringent restrictions of size, weight, efficiency, and surface temperature.

2. MATERIALS AND METHODS

2.1 Establishing an automated pipeline for optimization

A pipeline was created that connects existing software applications to automate the optimization process (Figure 1.) This pipeline is connected using Python as an executive program that implements the transfer and modification of information from one application to the next. Each open-source application was chosen for its scriptability and cross-compatibility with one another and its ability to handle the necessary tasks: geometry creation, mesh generation, finite volume method (FVM), and post-processing results. The post-processed results then undergo sensitivity analysis to determine what modifications to the geometry are necessary to optimize the design further.

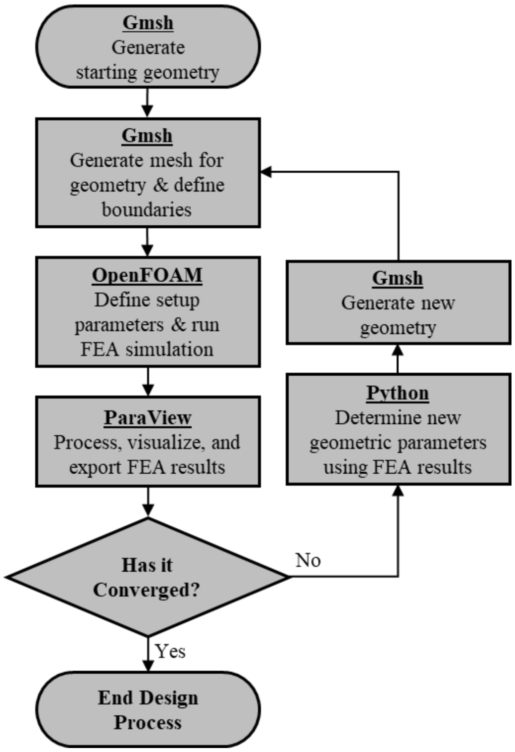

FIGURE 1: PIPELINE DIAGRAM OVERVIEW

2.2 Pipeline validation

A simplified case study was examined to validate the design pipeline: hydraulic pipe flow of ISO Grade Mineral Oil with a kinematic viscosity of 70 cSt through a pipe with a 90-degree bend. The optimization goal was to modify the flow path to reduce the pressure drop between the inlet and outlet of the pipe. The flow rate of the mineral oil was driven by a 15-mm diameter piston moving at 2 cm s^{-1} resulting in a flow rate of 3.5 $cm^3\ s^{-1}$ with an operating pressure of 1000 psi. The pipe had an inner diameter D of 5 mm and extended 20 D on both sides of a short-radius elbow with a radius of 0.5 D on the inside and 1.5 D on the outside (Figure 2).

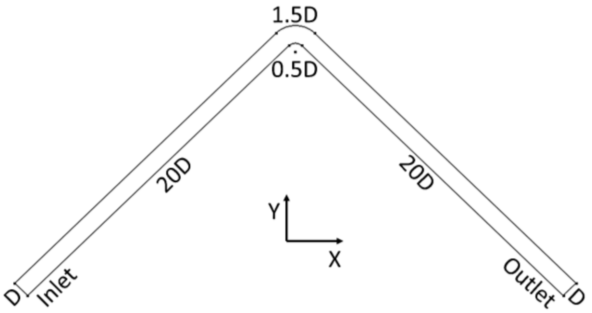

FIGURE 2: CONTROL CASE GEOMETRY – 90° PIPE BEND

The entrance length l_e used was above the minimum threshold for full-developed flow at 0.77 D (Equation 1) for laminar flow using a Reynolds number Re based on the fluid properties and flow conditions [11].

$$\frac{l_e}{D} = 0.06Re \tag{1}$$

The geometry was modeled in two dimensions with a maximum surface mesh size of 0.08 mm with a geometric size-reduction towards the walls down to 0.008 mm to ensure convergence with a minimized computational time. The surfaces of the geometry were designated by three categories: pipe wall, inlet, and outlet.

The solver chosen for the finite volume method was SimpleFoam because it solves steady-state, incompressible flow problems using the equations for continuity and momentum given by

$$\vec{\nabla} \cdot \vec{u} = 0 \tag{2}$$

$$\vec{\nabla} \cdot (\vec{u} \times \vec{u}) - \vec{\nabla} \cdot \vec{R} = -\vec{\nabla} p + \vec{S}_u \tag{3}$$

where $\vec{u}$ is the velocity [m s^{-1}], p is the kinematic pressure [$m^2\ s^{-2}$], $\vec{R}$ is the stress tensor [$m^2\ s^{-2}$], and $\vec{S}_u$ is the momentum source [m s^{-2}].

As a result of using this solver, the required initialization parameters included setting the gauge kinematic pressure of the outlet to 0, the inlet velocity to 0.127 m s^{-1} (based upon the flow rate and cross-sectional area), and the pipe wall to a no-slip condition. The kinematic viscosity was set to 70 cSt, and all previously undefined boundaries were assigned to a zero gradient for kinematic pressure and velocity. In order to run a 2-D model, a single layer was extruded in the z-direction with the top and bottom of that layer set as an empty boundary so that OpenFOAM ignores propagation in this direction.

For solver control, OpenFOAM was set to a 20000-iteration cap with solutions written every 1000 intervals. The root-mean-square (RMS) residual targets for pressure and velocity were set to 10^{-8} with the solution scheme set to steady-state and laminar.

In ParaView, a plot line was generated down the axis, and the pressure and streamline velocity were exported as a function of path distance along the center of the pipe from the inlet. From here, Python was used to determine the kinematic pressure drop across the pipe as a benchmark for convergence.

To reduce computational resources, the geometry used for optimizing the 90-degree pipe bend had a flow path described by a 7th order polynomial with the two ends matching the slope and position of the original inlet and outlet, providing four of the constraints on the polynomial function. The remaining polynomial constraints of the flow path were given by iterating through the x and y position of the bending point of the pipe (where the slope is 0), as shown in Figure 3. The pressure and velocity profile skews were used to determine the perturbation direction for the bend location along the flow path of the next geometry iteration. The perturbation amount was determined by assuming a unimodal variation along the x and y coordinates and implementing a golden ratio search.

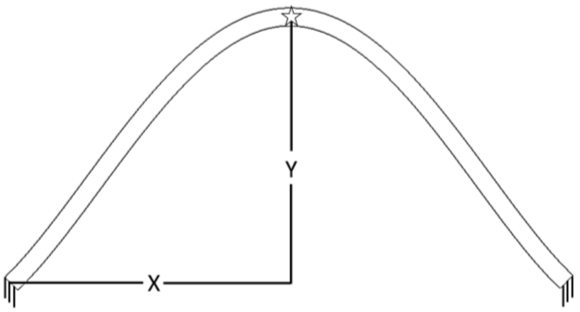

FIGURE 3: OPTIMIZATION GEOMETRY – ADJUSTABLE BEND LOCATION AND FIXED INLET AND OUTLET

3. RESULTS AND DISCUSSION

The control case resulted in a kinematic pressure drop of 1.3 $m^2 s^{-2}$, which can be attributed to the 90-degree bend in the pipe which deviated significantly from the desired flow path. The optimization process resulted in the pipe bend shifting downward by 74.3% of the original height of the control case and shifting right of center by 20.8% of the distance between the fixed inlet and outlet (Figure 4.) The optimized geometry is consistent with basic principles as more significant bends are considered non-ideal for flow, and this emphasized with higher velocities, which would result in a preference for the more substantial bend to be later in the flow path rather than earlier.

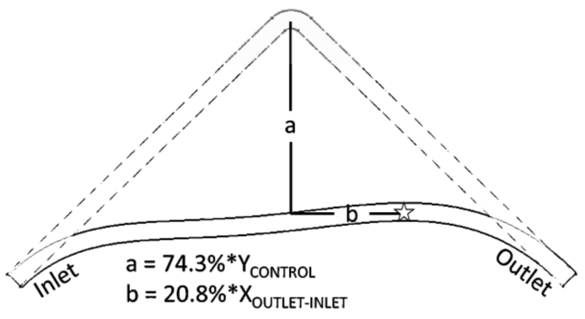

FIGURE 4: OPTIMIZED GEOMETRY

After optimizing the location of the bend in the y-direction, the kinematic pressure drop was reduced by 36.6±0.7% and reduced by an additional 1.9±0.4% upon adjusting the x-direction for seven iterations each (Figure 4). This reduction in pressure drop is correlated to the losses in efficiency. This loss in efficiency is vital for small-scale systems because it corresponds to a required increase in battery size to compensate for the energy lost.

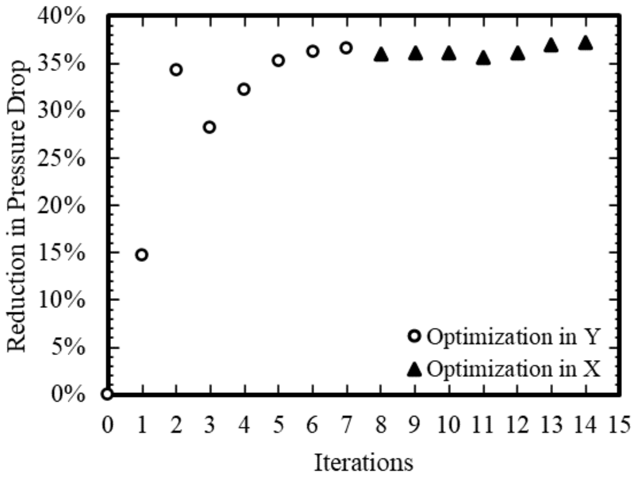

FIGURE 4: ITERATIVE REDUCTION IN PRESSURE DROP

The pressure drop is a linear function of flow path position, as shown in Figure 5, where the top line corresponds to the control case with a shallower slope with each iteration.

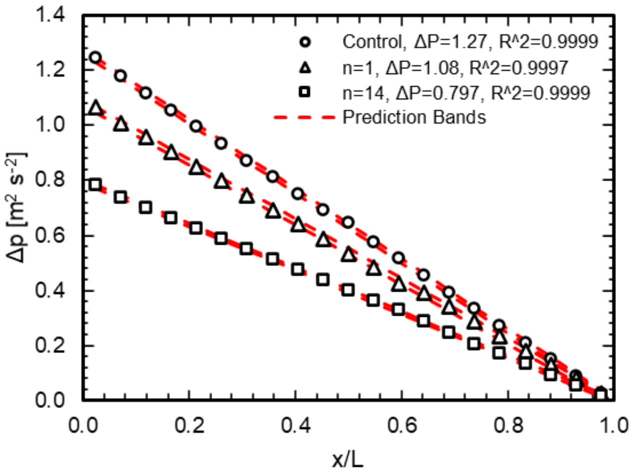

FIGURE 5: OPTIMIZING STREAMLINE PRESSURE DROP

Another property of this pipeline is computation time. Since the intention of this pipeline is to be iterative, it is essential that the iterations are not computationally expensive and, therefore, offer reasonable timelines for achieving an optimized design. The time expenditure can be broken into two categories: the solver time and the rest of the operations. The time for the non-solver operations was negligible compared to the solver time ranging between 10 and 12 seconds. On the other hand, the solver time was significant and took 30.9±1.1 minutes per iteration when run on a single processor. Increased processing capability, as would be the case when using a supercomputer, would reduce this time. The compilation time and the solver time can be reduced by reducing the number of elements found within the mesh; however, this can come at the cost of accuracy and may prevent convergence. Relaxation factors can also play a significant role in convergence time through automation by using smaller values (corresponding to smaller step changes through solution iterations) during the initial and less stable trials and increasing these values as the residuals reduce in order to speed up the convergence with less concern of divergence.

While 2D models can significantly save computational time, they can come at the cost of accuracy and even the overall validity if the correct conditions are not met. For example, turbulent flow causes mixing in all three dimensions, which cannot be captured through 2D modeling. The geometry is another concern when the aspect ratio of the cross-sectional flow in the third direction is not significantly large because it allows the cross-sectional shape to impact the flow characteristics. In the case of this experiment, the flow conditions resulted in a fully laminar flow, which removes the issue of turbulence. However, the circular cross-section of a pipe would not provide the high aspect ratio required to ignore the third dimension. Therefore, the optimization results can only be used as a reference. The initial and final flow path was modeled in 3D, resulting in a pressure drop reduction of 24.6%. While this reduction in pressure drop is not as significant as what was predicted in 2D, the results indicate that optimization was successful. The pressure drop discrepancy can be attributed to the curvature of the pipe that is not captured in the 2D model, as opposed to the algorithm itself.

4. CONCLUSION

This study introduced a pipeline composed of open-source software applications whose operations and communications are facilitated by a Python script. When applied to a 90-degree pipe bend, the pipeline was shown to reduce the pressure drop by 37.2±0.4%, corresponding to an equivalent percentage in weight reduction from needing a larger battery due to the need to compensate for inefficiencies. While computational time remains a concern, the pipeline is viable for use in a multiphysics generative design algorithm. Future work will address computational time and incorporate custom solvers that combine structural mechanics, fluid mechanics, and heat transfer into a single solver that can optimize multiple parameters simultaneously.

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