# Multi-Physics and Multi-Objective Response Surface Based Design Optimization of a Control Valve

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## Introduction

A control valve is a flow control device typically used to regulate different types of flow. Currently the design of control valves is primarily carried out using traditional methods which have been well developed over the years.
Typical traditional valve design methodologies are based on existing specific valve design data with the assumption of geometry and flow characteristic similarities. These assumptions are the major limitations of traditional valve design methods; such that existing data cannot be accurately referenced in the case of different geometry profile trim being introduced into the valve.

Traditional approach of building few prototypes and measuring performance only assists in understanding a small fraction of the design space. One factor at a time (OFAT) experiments and simulations systematically vary one design variable at a time while holding the others constant and recording the impact on performance. The time required makes it practical only to cover a small fraction of the design space. This approach fails to account for the multiple factor interactions. These challenges have been addressed in this tool.

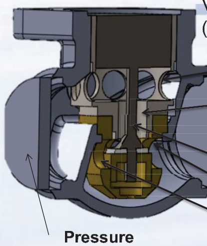
## Hypothesis & Objectives

We hypothesize that the response surface artificial neural networks (ANN) paragridm model can be successfully implemented in the control valve design tool, and can accurately predict the multi-physics and multi-objective target function output values at low cost.
Objectives:

- Develop a robust/ universal and automated control valve design tool.
- Determine the accuracy of the response surface neural network model in predicting the non linear and discontinuous flow field, and resulting fluid structure interaction (FSI) stress and deformation response.

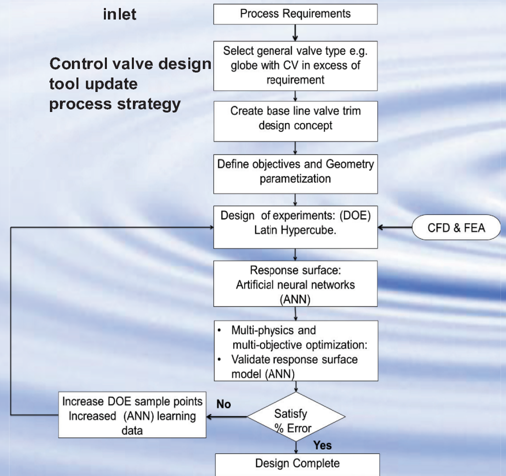
## Methodology

The response surface optimization of the control valve is implemented in the computational fluid dynamics (CFD) platform of Ansys, the fluid simulation tool is coupled with a finite element analysis tool (FEA) from which direct fluid structure interaction response is determined.

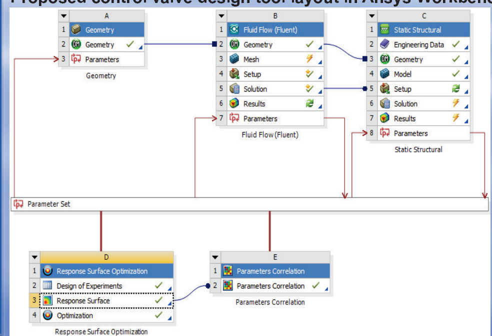


Valve baseline design concept (CFD) /(FEA) simplified.
Top cage flow holes Diameter
Top cage flow holes Diameter
Pressure outlet
Stem Outside diameter
Vena contracta region
Bottom cage flow holes
Pressure inlet

Control valve design tool update process strategy




Proposed control valve design tool layout in Ansys Workbench



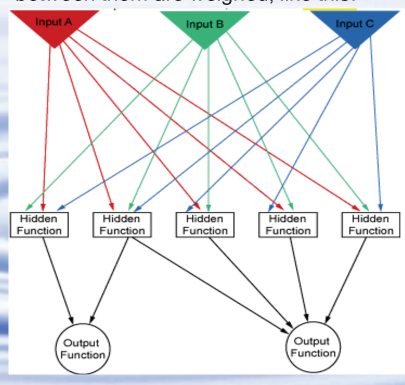

## Methodology

### Design of Experiments (DOE)

The Latin Hypercube Sampling Design DOE type has been implemented in this tool, The DOE is generated by the LHS algorithm, an advanced form of the Monte Carlo sampling method that avoids clustering samples.. The user defined sampling type has been used in this tool with an initial 30 sample design points.

### Response Surface : Artificial Neural Networks (ANN)

This mathematical technique is based on the natural neural network in the human brain. In order to interpolate a function, we build a network with three levels (Input, Hidden, Out) where the connections between them are weighed, like this:




## Methodology

### Optimization:

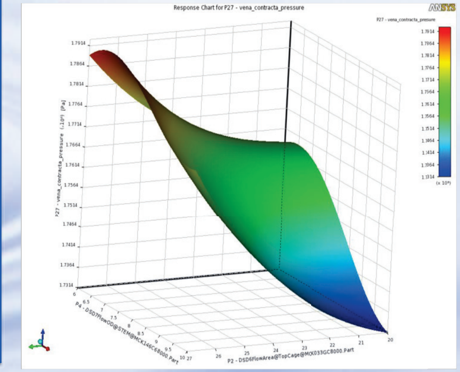
The Screening approach has been used in this tool to find the target output objective values. The screening approach is a non-iterative direct sampling method by a quasi-random number generator based on the Hamersley algorithm.

### Objectives and constraints

| Parameter | Objective | | Constraint | | |
|---|---|---|---|---|---|
| | Type | Target | Type | Lower Bound | Upper Bound |
| P19 - Total Deformation Maximum | Minimize | | No Constraint | | |
| P18 - Equivalent Stress Maximum | Minimize | | No Constraint | | |
| P26 - CV | Seek Target | -13 | Lower Bound... | -14 | -10.5 |
| P27 - vena_contracta_pressure | Seek Target | 1.3E+05 | Lower Bound... | 1.2E+05 | 1.4E+05 |

## Results

Detailed response surface plots at low cost giving insight into multiple factor interaction.




### Table of (ANN) response surface design target predictions and verified results with % error

| Name | IINPUT VARIABLES: Bottom cage flow holes P1 (mm) | Top cage internal flow diameter P2 (mm) | Top cage flow holes P3 (mm) | Stem outside diameter P4 (mm) | Pressure outlet P20 (PSI) | OUTPUT OBJECTIVE VALUES: Volume flow rate output P11 (m^3/sec) | % Error | Equivalent stress P18 (N/m^2) | % Error | Total deformation P19 (mm) | % Error | Force Stem P22 (N) | % Error | CV P26 (USGPM) | % Error | Vena contracta pressure P27 (N/m^2) | % Error | Vena contracta velocity P29 (m/sec) | % Error |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Candidate Point 1 | 16.3 | 25.5 | 13.8 | 9.3 | 32.1 | 0.0 | | 9954813.4 | | 0.0111 | | 1126.7 | | 12.3 | | 129985.9 | | 34.0 | |
| Candidate Point 1 (verified) | 16.3 | 25.5 | 13.8 | 9.3 | 32.1 | 0.0 | 1.3 | 8709586.8 | 12.5 | 0.0071 | 40.9 | 1080.5 | 4.1 | 12.5 | 1.3 | 78347.4 | 39.7 | 38.4 | 11.5 |
| Candidate Point 2 | 16.7 | 24.4 | 16.5 | 8.9 | 25.3 | 0.0 | | 8382851.7 | | 0.0119 | | 1054.1 | | 11.7 | | 139757.1 | | 39.1 | |
| Candidate Point 2 (verified) | 16.7 | 24.4 | 16.5 | 8.9 | 25.3 | 0.0 | 1.6 | 9067244.3 | 7.5 | 0.0081 | 32.3 | 1059.8 | 0.5 | 11.9 | 1.6 | 149579.0 | 6.6 | 25.7 | 34.1 |
| Candidate Point 3 | 14.5 | 24.6 | 14.9 | 8.8 | 13.8 | 0.0 | | 10216840.1 | | 0.0088 | | 1107.9 | | 11.0 | | 137307.6 | | 30.8 | |
| Candidate Point 3 (verified) | 14.5 | 24.6 | 14.9 | 8.8 | 13.8 | 0.0 | 2.6 | 9138517.2 | 10.6 | 0.0069 | 21.4 | 1112.9 | 0.4 | 11.3 | 2.6 | 50971.7 | 62.9 | 23.7 | 23.0 |
| Candidate Point 4 | 16.0 | 25.8 | 15.3 | 8.0 | 30.5 | 0.0 | | 13544785.5 | | 0.0158 | | 1195.4 | | 12.5 | | 123724.8 | | 38.9 | |
| Candidate Point 4 (verified) | 16.0 | 25.8 | 15.3 | 8.0 | 30.5 | 0.0 | 2.5 | 12317079.7 | 9.1 | 0.0136 | 13.7 | 1200.3 | 0.4 | 12.9 | 2.5 | 156521.5 | 21.0 | 25.2 | 35.2 |

## Conclusion:

A multi-physics and multi-objective control valve design tool has been proposed .The artificial neural networks response model has accurately predicted the multiple objective and multi-physics target design outputs within a small % error with validation results. The proposed tool can be successfully used in the design and optimization of control valves at very low cost of computational analysis and time to results.