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Multi-objective optimization based engineering decision tool

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by

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ABSTRACT

Prior to the acceptance of computer aided engineering (CAE) software in the product development process (PDP), product development was characterized by a design-test-redesign-test cycle. This activity was time consuming and resource intensive. As CAE software tools have been integrated into the PDP, the PDP can be characterized by a design-simulate-redesign-test cycle. The addition of CAE tools to the PDP has reduced the time to market and resource consumption.

In the last decade, CAE software has become easier to use and computer power has increased such that CAE software is more widely used in the PDP. In parallel, there has been a desire, in the last decade, to further reduce product development times and resource consumption. To achieve this next step in reduction of PDP time and resource consumption, the need for increased integration of CAE software earlier in the PDP is needed. This will provide the design engineer with increased design problem knowledge earlier in the PDP, which is when increased knowledge about the design problem is most valuable in the PDP timeline and can impact the product design the most. Design problems are characterized by having multiple solutions. The implication of this is that there are multiple acceptable solutions but there are few global optimum solutions. It is the design engineer's chief aim to find the most optimum solution to the design problem at hand.

Simply put, the aim of the method presented in this thesis is to *integrate computational fluid dynamics (CFD) models earlier in the PDP to facilitate engineering decision making early in the PDP.*

In this thesis, a simulation workflow is demonstrated that connects computer aided design (CAD) software with CFD software, which is a CAE software, with both connected to a multi-objective optimization algorithm. This simulation workflow is used to generate a Pareto-optimal set of designs, sometimes called non-dominant, set of designs. The design problem is represented in the CAD software with the geometric design variables explicitly defined in the CAD representation of the design problem. The CFD software is used to calculate the performance objectives of the design solution. The multi-objective optimization algorithm evaluates the performance of the design solution and chooses new design variable values for use in the CAD representation. This process continues until the Pareto-optimal set of designs is identified. This is the Level-1 optimization of the overall framework presented in this thesis. The Level-2 optimization consists of an algorithm that operates on the Pareto-optimal set of designs identified in the Level-1 optimization. The algorithm presents the user with a number of designs from the Pareto-optimal set. The user chooses the best design solution from the design solutions shown based on higher-level, qualitative information. This continues until all of the Pareto-optimal designs have been evaluated or the user terminates the process.

This simulation flow facilitates using CAE software, specifically CFD, earlier in the PDP which leads to simulation based design. This maximizes design problem

knowledge earlier in the PDP, reduces the PDP time, and reduces the resources required to develop a new product.

CHAPTER 1 : BACKGROUND AND LITERATURE REVIEW

In this chapter, an overview of the thesis is presented, along with a focused review of the pertinent literature.

1.1 Background

Engineering design problems have the characteristic that they are ill posed in that there are often many solutions to the design problem. In engineering design often all of the constraints are not known for the design solution, which leads to the design problem being ill posed. In the extreme case, where all of the constraints and acceptance criteria are defined in great detail, the problem is an analysis problem not a design problem. In product design it is desirable to think outside the box with few constraints with the goal to generate a wide range of ideas, whereas in design analysis the constraints and acceptance criteria must be specified so that a particular design solution can be evaluated. The method presented in this thesis seeks to bridge the gap between design problems and engineering analysis problems. This thesis focuses on developing simulation workflows (simulation flows) that allow the engineer to specify the constraints and acceptance criteria of a engineering component (inlet tank, jet pump, etc) and use CFD models

coupled with multi-objective optimization algorithms to determine a set of Pareto-optimal (non-dominated) set of design solutions to the engineering design problem.

This is helpful in the traditional mechanical design process because this simulation workflow will allow the engineer to evaluate various Pareto-optimal design solutions to a design problem. The utility of this is that, as the design progresses through the PDP additional constraints or more details about existing constrains will become known. With a set of design solutions that meet a set of known constraints and acceptance criteria, the engineer can then start to determine what design solutions best meet the new or more detailed constraints. Secondly there exists higher-level information (which is often qualitative) that is part of the PDP. This higher-level information is often difficult to model and often subjective. Things like aesthetic appearance, customer acceptance, perceived ride quality, perceived environmental friendliness are examples of higher-level information that needs to be considered during the PDP. With a set of design solutions that meet the requirements of the design problem, the engineer can evaluate these design solutions against the higher-level information thus making an engineering decision based on design solutions that meet the required constraints while choosing the correct design solution to meet the higher-level requirements also.

Detailed computational software exists to analyze the work, heat, and mass transfer mechanisms and the associated energy flow of engineered internal flow devices. Many different software packages are best suited for a particular set of problems. These software packages are well developed and have been shown to accurately calculate the

physics of various problems (ANSYS® 2010). With that said the method presented in this thesis does not propose to develop any new analysis package rather, the aim is to integrate each specialized software package together within one software framework in a way that allows the specialized software to couple with multi-objective algorithms as well as develop a Level-2 optimization algorithm that facilitates engineering decision making. This linking will allow various specialized software packages to be used throughout the PDP with the intent to determine a set of Pareto-optimal design solutions based on constraints and acceptance criteria. To meet this need, a framework is built on the simulation automation and optimization software Isight (SIMULIA 2011). The Level-2 optimization algorithm, which assists the engineer in making decisions regarding design solutions, is developed in the C++ computer language.

To properly describe an optimization problem design variables, constraints, and an objective function(s) (sometimes called the cost function) must be defined. Design variables are parameters chosen to describe the design solution of a system. An example of a design variable is the width and height of a heat exchanger. Design variables can be viewed as free to the extent that the engineer can change the value of the design variables within the bounds set by constraints. Consider the design of a pipe with an outer diameter *do*, inner diameter *di*, and a thickness *t*. A design solution could be formulated whereby *do*= 12mm, *di*= 10mm, and *t* = 2mm but this would violate the physical requirement that $t = 0.5*(do - di)$. If the problem is formulated *do*, *di*, and *t* as design variables the constraint that $t = 0.5*(do - di)$ must also be imposed. Once all of the design variables are assigned numerical values the design of the system is fixed. If the

design variables meet the required constraints the design solution is feasible. If a constraint is violated the design solution is infeasible. The feasible design solution can then be evaluated to understand the response to the imposed external affects (heat applied in the case of a heat exchanger). An important first step is the proper formulation of the optimization problem is to identify the design variables of the system. The following considerations should be given while defining design variables for a problem:

1. Design variables should be independent of each other as much as possible.
2. There is a minimum number of design variables required to formulate a design problem correctly.
3. It is good to designate as many independent parameters as possible as design variables at the initial design problem formulation phase. Later on, some of the design variables can always be given a fixed value.

There exist many combinations of design variables that produce a feasible design of a system. Some of these design solutions are better than others. To make this judgment a metric is required to compare the various design solutions. This metric must be a scalar function whose numerical value can be obtained once all of the design variables for the design solution are specified (the metric must be a function of the design variables). This metric is called an objective function for the design solution. Sometimes this is called the system or design solution response to the design variables. In the literature the objective function is called a cost function when the objective is to minimize the objective function. In essence the objective is what is desired like minimum cost, maximum efficiency, minimum deflection, etc. In the case where there

are multiple objectives that are desired (minimum cost, maximize efficiency, etc) these problems are referred to as multi-objective optimization problems. One method for working with multi-objective optimization problems is to form a composite objective function for the problem by assigning weighting values to each of the objectives and combining all of the objectives into one objective function. Another method is to select the most important objective and treat all other objectives as constraints. A third method where each objective is considered independently of the other objectives will be presented later, which is the method used in the framework presented in this thesis.

All of the restrictions placed on a design solution are collectively called constraints. Design solutions that violate any constraint are infeasible design solutions and design solutions that meet the constraints are called feasible design solutions. Each constraint must be influenced by one or more design variables; otherwise the constraint does not impact the optimum design solution. Some constraints are simple, such as the minimum or maximum of a design variable. Other constraints are implicit in that they depend on the design of the system. An example of an implicit constraint is the deflection at a particular point in a large structure. The deflection will be dependent on the design variables and cannot be written as an explicit function of the design variables except in the case of the simple structures. Linear constraints are those that only contain first order terms while all others are non-linear constraints.

Often in product design there exists equality and inequality constraints. An equality constraint might be that the fluid exiting a heat exchanger must be a given temperature. An example of an inequality constraint would be that the pressure drop

through the heat exchanger may be less than or equal to a given value. Inequality constrains always generate a larger design space than equality constraints.

Following is a standard model of single-objective optimization that many single-objective problems can be formulated as. This is helpful because with a standard model the same solution algorithms can be used to solve problems from different fields of study. The standard single-objective optimization model is defined as follows: Find a vector **x** = (x_1, x_2, …, x_n) of design variables to minimize an objective function, shown in Equation 1,

$$f(\mathbf{x}) = f(x_1, x_2, \ldots, x_n)$$

Equation 1: Standard model of single objective function.

subject to the *m* inequality constraints, shown in Equation 2,

$$g_i(\mathbf{x}) = g_i(x_1, x_2, \ldots, x_n) \leq 0; i = 1 \text{ to } m$$

Equation 2: Standard model inequality constraints.

and subject to *p* equality constraints, shown in Equation 3,

$$h_j(\mathbf{x}) = h_j(x_1, x_2, \ldots, x_n) = 0; j = 1 \text{ to } p$$

Equation 3: Standard model equality constraints.

where p is the total number of equality constraints, and m is the total number of inequality constraints.

The following items should be understood about the standard model of optimization:

1. The functions $f(\underline{x})$, $h_j(\underline{x})$, and $g_i(\underline{x})$ must depend on some or all of the design variables.
2. The number of independent equality constraints must be less than or at the most equal to the number of design variables, i.e. $p \leq n$.
3. Note that the inequality constraints in Equation 5 are written as less than or equal to zero. Greater than or equal to constraints can be converted to less than or equal constraints by transferring the right hand side to the left hand side. A greater than or equal to constraint can be converted to less than or equal to constraints by multiplying them by -1.
4. Some design problems may not have any constraints. These are unconstrained optimization problems, while the others are constrained optimization problems.
5. If all of the functions $f(\underline{x})$, $h_j(\underline{x})$, and $g_i(\underline{x})$ are linear in design variables **x** then the problem is called a linear programming problem. If any of the

functions is nonlinear the problem is called a nonlinear programming problem.

6. If the objective function is scaled by multiplying it with a positive constant, the optimum design solution does not change. The optimum objective does change, but not the design solution. Also, any constant can be added to the objective function without affecting the optimum design solution. The inequality constraints can be scaled by any positive constant, and equality constraints can be scaled by any constant. None of these scaling affect the optimum design solution (Arora, J. S. 1989).

As the name suggests multi-objective optimization problems deal with more than one objective function. In most engineering design problems, multiple objectives are present and often these objectives are conflicting. Because of the lack of suitable solution methodologies that maintain the independence of the multiple objectives, multi-objective optimization problems have been cast and solved as single-objective optimization problems in the past. The fundamental difference between a single-objective and multi-objective optimization problem is that the single-objective optimization problem is seeking to find one solution to the optimization problem (except in the case of a multi-modal optimization problem with multiple optimal solutions). A multi-objective optimization problem may not have the task to find one optimal solution to each objective function, rather a Pareto-optimal set of solutions is desired. In problems with two or more conflicting objectives, there is no single optimum solution. There exist a number of solutions, which could be the optimal. In the absence of additional

information, no solution from the set of Pareto-optimal solutions can be said to be better than any other. The task of the multi-objective optimization algorithm is to find an accurate representation of the objective surface or curve to present to the engineer (Fleming, P. J., Purshouse, R. C., Lygoe, R. J. 2005). Another difference between single-objective optimization and multi-objective optimization is that the objectives in the multi-objective problem form a multi-dimensional objective space in addition to the multi-dimensional decision (or design variable) space. In single-objective optimization the objective space is one-dimensional because there is one objective function.

From a practical standpoint a user needs only one solution to a problem, regardless if the problem is multi-objective or single-objective. In the case of a multi-objective optimization problem the user now needs to determine which of the optimum solutions to pick from. This is where the user needs to use the higher level, qualitative information to facilitate making the decision on which solution to choose. The ideal multi-objective optimization procedure can be described as follows:

Step 1: Find multiple Pareto-optimal solutions with a wide range of values for objectives.

Step 2: Choose one of the obtained solutions using higher-level information (Deb, K. 2001).

Multi-objective optimization problems have the characteristic that they have multi-dimensional objective space, which many design problems also exhibit. This makes multi-objective optimization an excellent candidate method for determining the multiple optimum design solutions to a design problem. This application of multi-

objective optimization to engineering design problems uses a physics based model (deterministic model) to evaluate the various combinations of design variables to determine a system response, which becomes part of the objective to be minimized or maximized. The framework presented in this thesis generates the multiple tradeoff solutions (Pareto-optimal solutions) by using commercial software to perform the CFD calculations to evaluate the design solution and generate the CAD representation of the design solution with Isight as the simulation workflow execution engine and optimizer.

1.2 Overview

This section provides an overview of the research method used to solve the problem of *integrating CFD models earlier in the PDP to facilitate engineering decision making early in the PDP*. To solve this problem a multi-objective, multi-level optimization framework is used whereby CAD models and CFD models are exploited to search the design space to find the Pareto-optimal design solution set (Level-1) and a user in the loop optimization algorithm searches the Pareto-optimal design solution set to determine which Pareto-optimal design solution is the optimum solution (Level-2). Figure 1 illustrates the above outlined method for achieving a multi-objective based engineering decision tool.

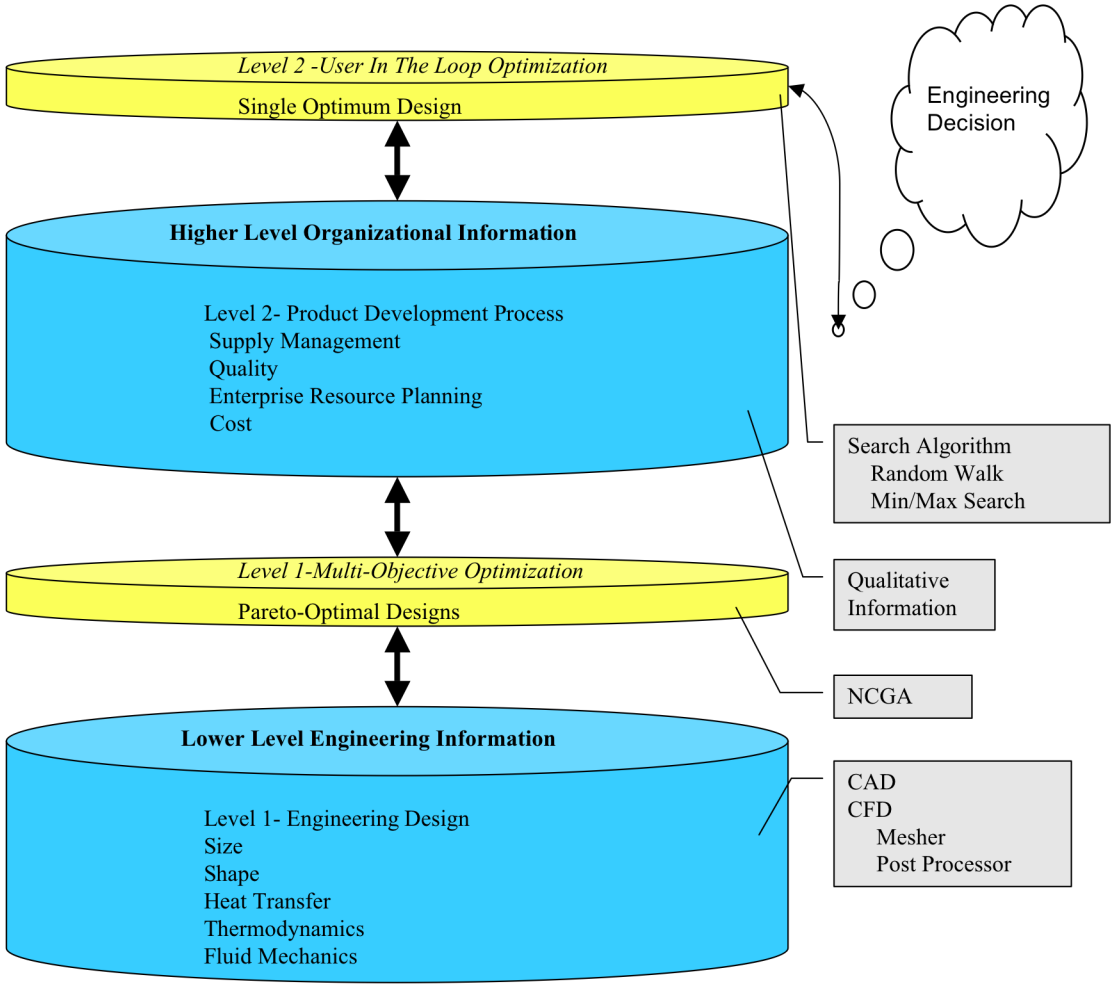

Figure 1: Schematic of multi-level method.

At the lower level (Level-1) there exists engineering design information which includes the functional requirements and design parameters present in a design solution. Items like size, shape, length, heat transfer, pressure drop are examples of the information that are contained at this level. In the method presented in this thesis, the geometric and mass property items are represented in CAD software and the heat transfer, thermodynamic, conservation of mass, and fluid mechanics items are represented in CFD

software. The combination of the CAD and CFD software allow for the various design solutions to be evaluated. Items like pressure drop, induced flow, and uniformity index are examples of functional requirements. The CAD software used in this framework is Pro/ENGINEER®, the CFD meshing software used is ANSYS® mesher, and the CFD solver used is ANSYS® FLUENT™.

Design problems have the characteristic that there are often many solutions to a given design problem (CHAPTER 3 contains more information on this concept). The Level-1 multi-objective optimization workflow is the method that is used to exploit the design space to find the Pareto-optimal design solutions. The framework presented in this thesis uses the neighborhood cultivating genetic algorithm (NCGA) to generate the Pareto-optimal design solution set. CHAPTER 4 contains detailed information on the neighborhood cultivating genetic algorithm. The simulation workflow software that is used to connect the CAD, CFD, and NCGA is Isight. Once the Pareto-optimal design solutions are determined, the Level-2 optimization algorithm is run. The Level-2 optimization algorithm utilizes the user to evaluate the fitness of each design presented to the user with the chief aim to assist the user in determining the most optimum design solution.

The multi-objective optimization based engineering decision tool presented in this thesis is demonstrated on three example cases.

Case 1 demonstrates the design of a tube and fin, liquid to air heat exchanger fin that maximizes the heat transfer from the liquid to the air with the minimum air side pressure drop. Kays, W., M., London, L., A. (1984) illustrates the function and various

design and performance considerations for liquid to air heat exchangers. This study was initiated to facilitate future heat exchanger technology negotiations between an Original Equipment Manufacturer (OEM) of off-road equipment and a heat exchanger manufacturer, not as a detailed design study of heat exchangers by the OEM. The OEM system engineer initiated the optimization activity. When the optimization activity is initiated, the manufacturing engineer and performance engineer do not have models to integrate into the Level-1 optimization simulation workflow to evaluate manufacturability or debris tolerance of a given design solution. The decisions related to these constraints are left for the Level-2 optimization.

Figure 2 shows a representative tube and fin arrangement of a tube and fin heat exchanger. The liquid flows through the tube and the air flows through the passage created by the fin and tube walls. The heat flows from the liquid to the tube, then to the fin, and finally to the air. A heat exchanger is composed of many fins and tubes soldered together with a top and bottom plate and associated liquid tanks. For this study a single air passage is studied.

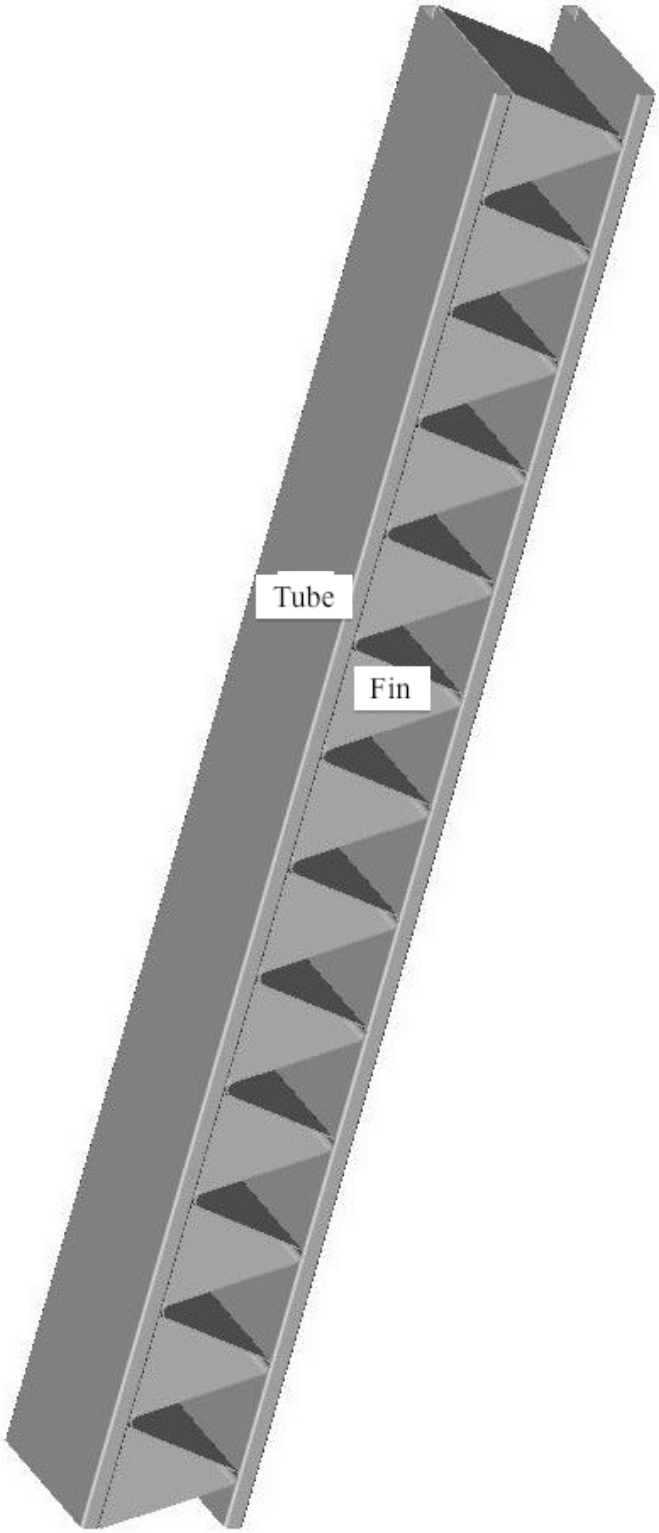

Figure 2: Case 1 fin design problem.

Figure 3 shows the CFD domain that is created by the fin and tube passage including the pertinent design variables for this case, which are the radii and flat length of the fin.

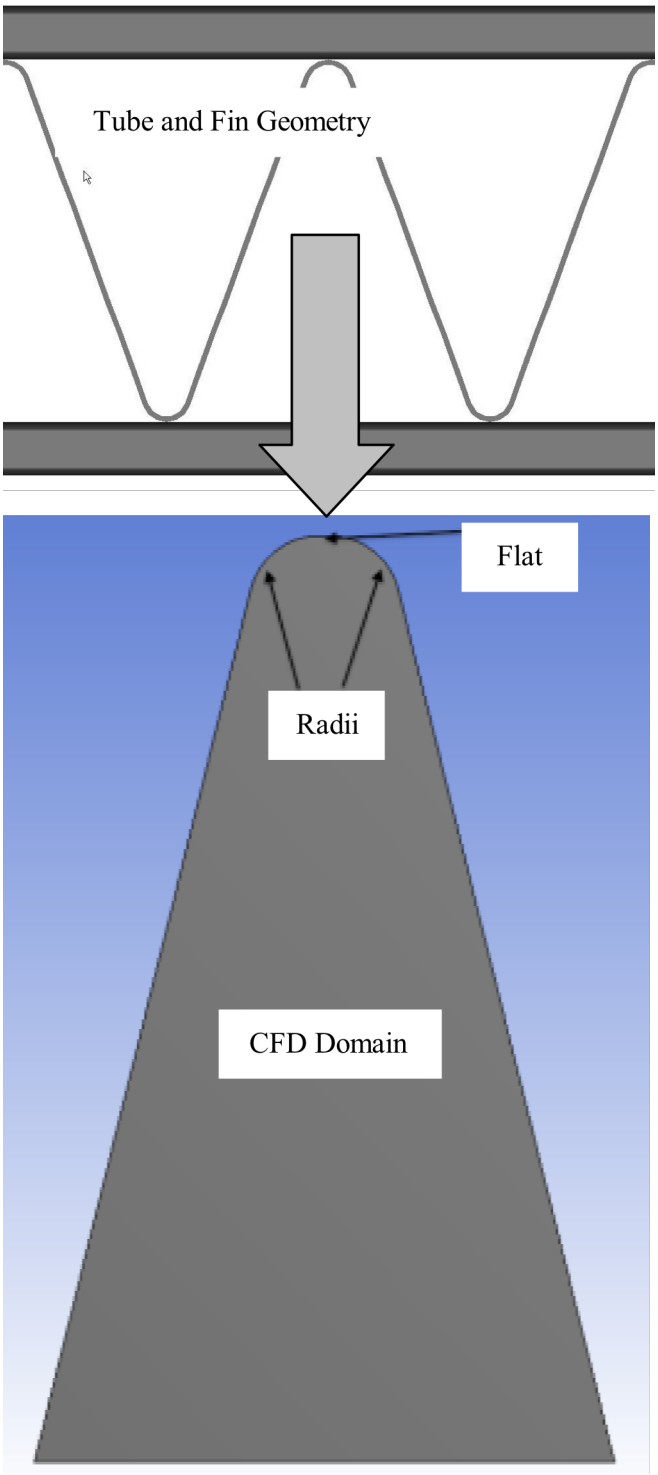

Figure 3: Case 1 design variables.

The radii can vary between 0.5mm and 2.4 mm and the flat can vary between 0.1 mm and 4 mm. Table 1 shows the boundary conditions for this case.

Table 1: Case 1 CFD model boundary conditions.

Boundary Condition	Units	Value
Inlet Velocity	m/s	10
Inlet Temperature	C	25
Wall Temperature	C	100
Outlet Pressure	kPa	100

Case 2 demonstrates the design of a jet pump that is used to induce a secondary flow by passing a primary flow through a nozzle that is immersed in a larger pipe as shown in Figure 4.

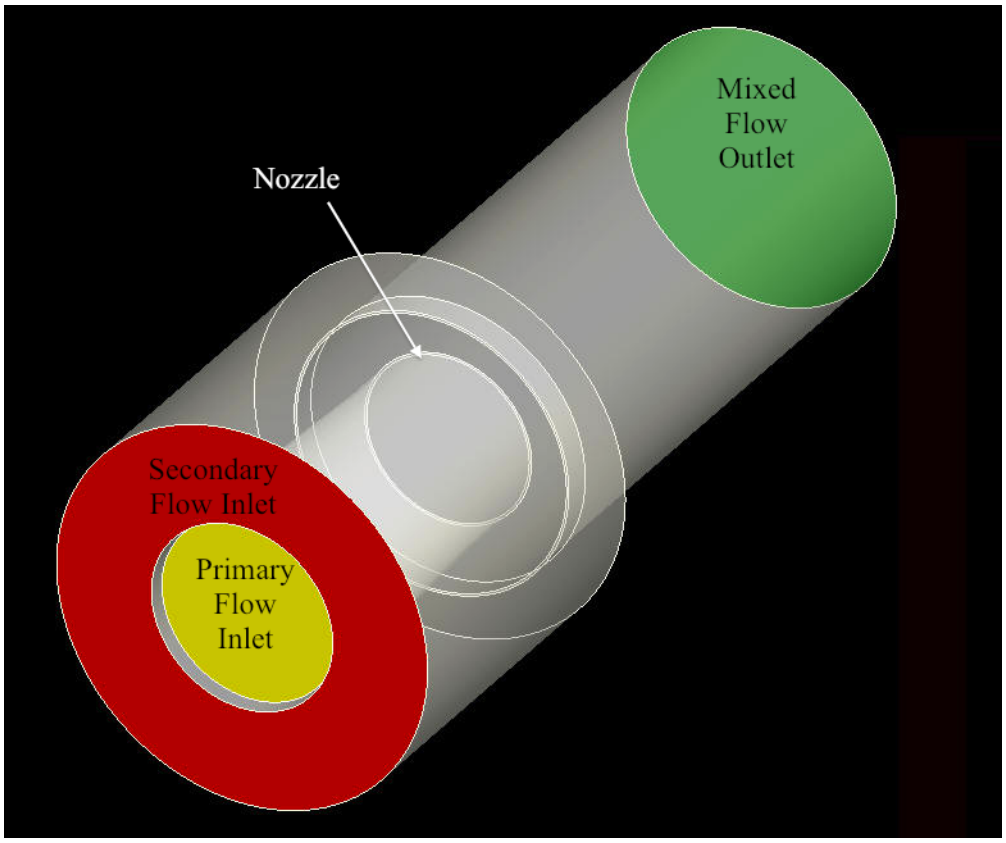

Figure 4: Case 2 jet pump design problem.

Jet pumps have been used in various applications similar to this as shown in Priestman, G. H., Tipetts, J. R. (1995), Long X., Yan H., Zhang S., Yao X. (2010), Beithou N., Aybar H. S. (2001), Fairuzov Y., Bredikhin V. (1995), Lorra M. A., Smith, J., Bussman W., Webster, T. (2001).

The design problem is to design a jet pump that minimizes the total pressure drop between the mixed flow outlet and the primary flow inlet while maximizing the mass flow into the component through the secondary flow inlet. Figure 5 shows the design

variables that are changed in this case and Table 2 shows the boundary conditions for the CFD model.

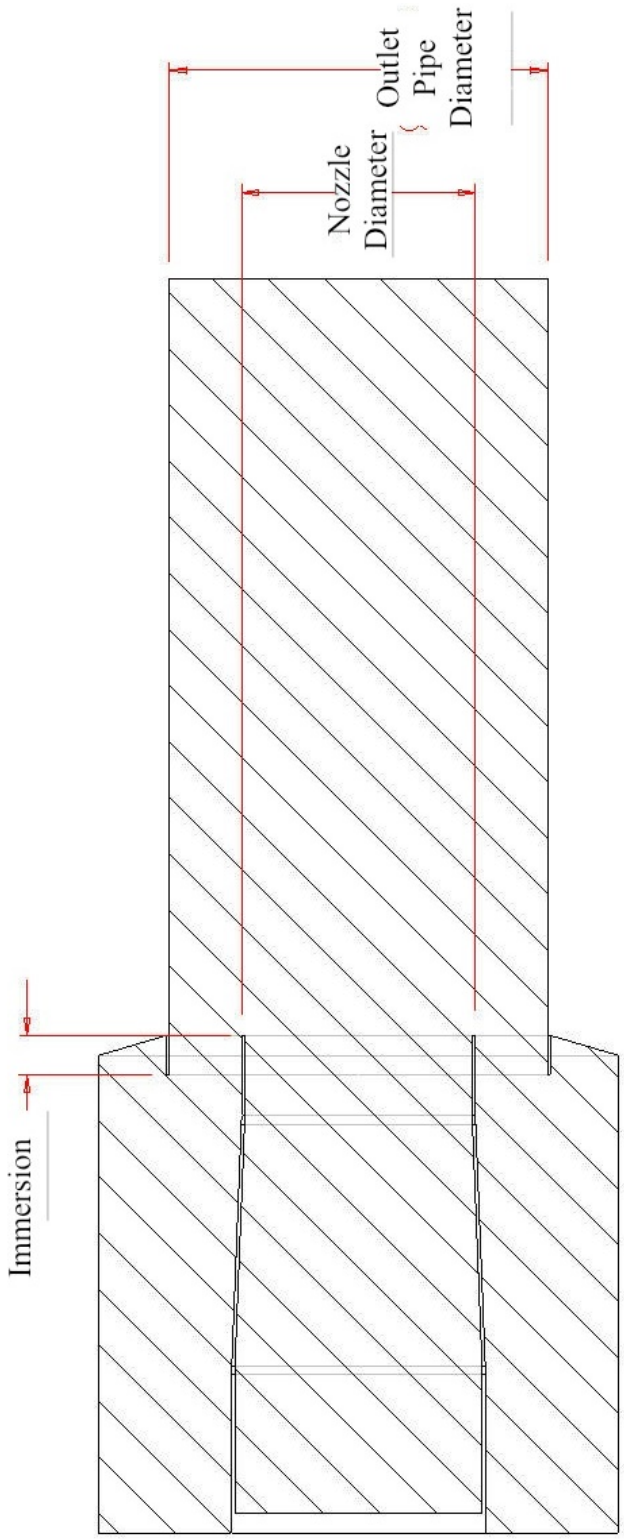

Figure 5: Case 2 design variables.

Table 2: Case 2 CFD model boundary conditions.

Boundary Condition	Units	Value
Primary Inlet Mass Flow Rate	kg/hr	1400
Primary Inlet Flow Temperature	C	650
Mixed Flow Outlet Pressure	kPa	100
Secondary Flow Inlet Pressure	kPa	100
Secondary Flow Inlet Temperature	C	120
Wall Heat Flux	w/m^2	0

To solve this design problem Pro/ENGINEER® was used to generate a CAD representation of the jet pump. ANSYS® mesher and ANSYS® FLUENT™ were used as the mesh generation software and CFD solver to perform the CFD calculations to generate the pressure drop values and secondary mass flow for the various combinations of the design variables. Isight was used as the optimizer and the simulation workflow execution engine. This CFD model requires approximately 0.52 hours to run one design case, which requires that a response surface model be generated and used by the multi-objective optimizer.

Case 3 demonstrates the design of an inlet tank of an exhaust system device that maximizes the mass flow uniformity index at the tank outlet and minimizes the total pressure drop of the tank as shown in Figure 6. The design variables for this design problem are the inlet radius, perforated plate height, and the perforated plate hole diameters.

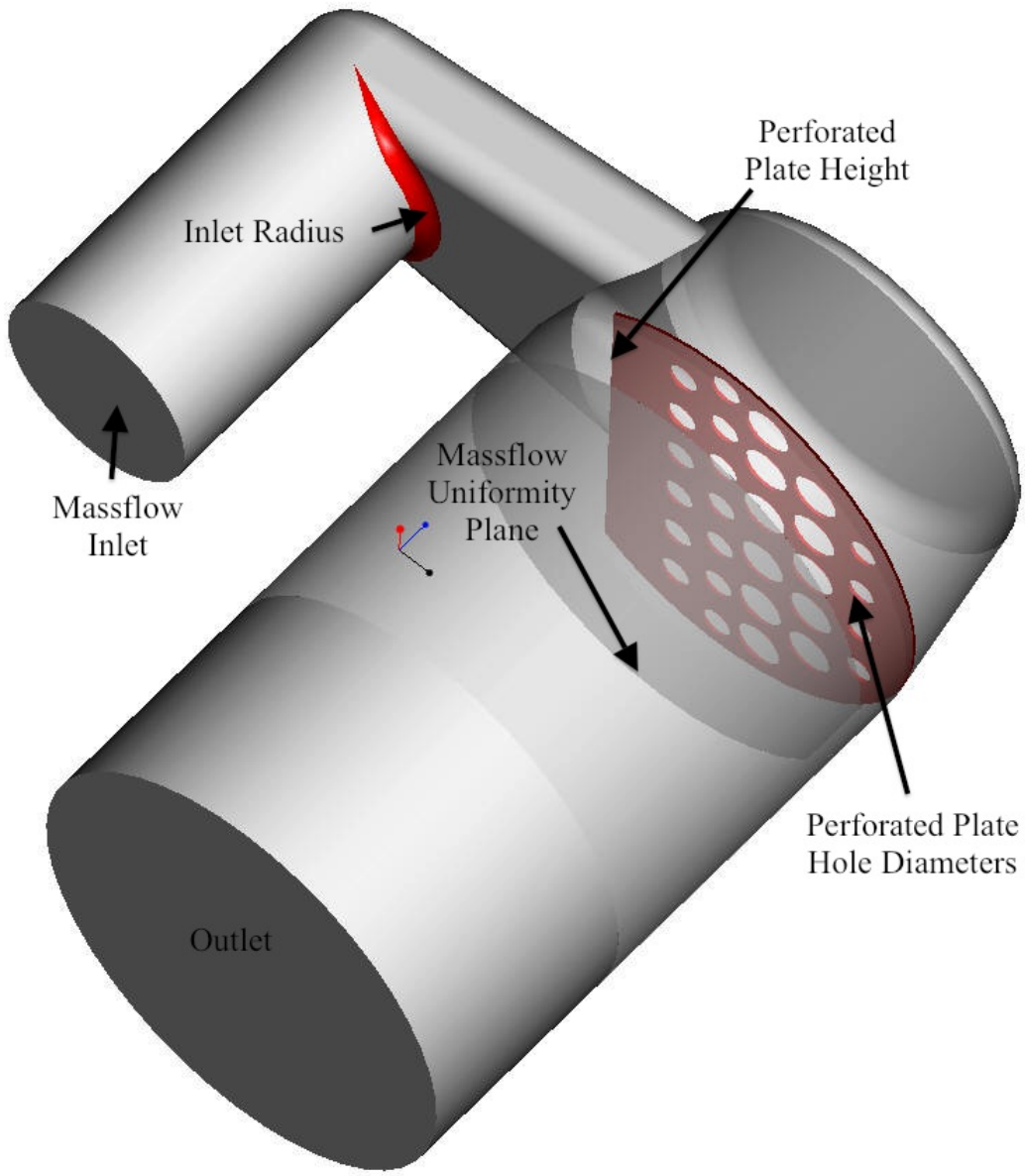

Figure 6: Case 3 example design problem.

The boundary conditions for this case are shown in Table 3.

Table 3: Case 3 CFD model boundary conditions.

Boundary Condition	Units	Value
Inlet Mass Flow Rate	kg/hr	1400
Inlet Temperature	C	650
Outlet Pressure	kPa	100
Wall Heat Flux	w/m^2	0

This case uses the same simulation workflow as Case 1, with the appropriate CAD model, meshing parameters, and CFD solver settings as well as the appropriate design variables and objectives.

1.3 Literature Review

In this section a review of the pertinent literature is presented. The previous sections and following chapters are built on the current base of literature in a broad view. This section will specifically focus on the literature that is pertinent to the details of the method presented in this work.

In Merkel, M., Schumacher, A. (2003) a method is presented that uses CAD, FEA, and multi-objective optimization algorithms to develop an optimized design of a vehicle steering knuckle as shown in Figure 7.

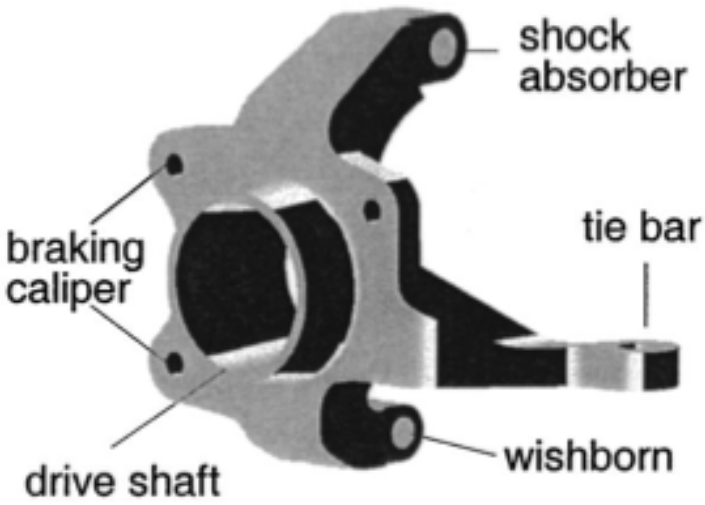

Figure 7: Steering knuckle. (From Merkel, M., Schumacher, A. (2003)).

This method uses the CAD system UniGraphics which is capable of generating 3-Dimensional representations that are parametric and non-parametric. The workflow presented in Merkel, M., Schumacher, A. (2003) requires that the design space be parameterized. The interface between the CAD and CAE software is PARASOLID, which is available in many commercial CAD and CAE software tools. MSC/PATRAN is used to build the finite element analysis (FEA) mesh and define the loads and boundary conditions. MSC/NASTRAN is used to solve the linear elastic FEA model and LMS/Falancs is used to perform the fatigue analysis. The simulation workflow and optimization software LMS/Optimus is used to manage the optimization simulation flow. Figure 8 shows the workflow of this method.

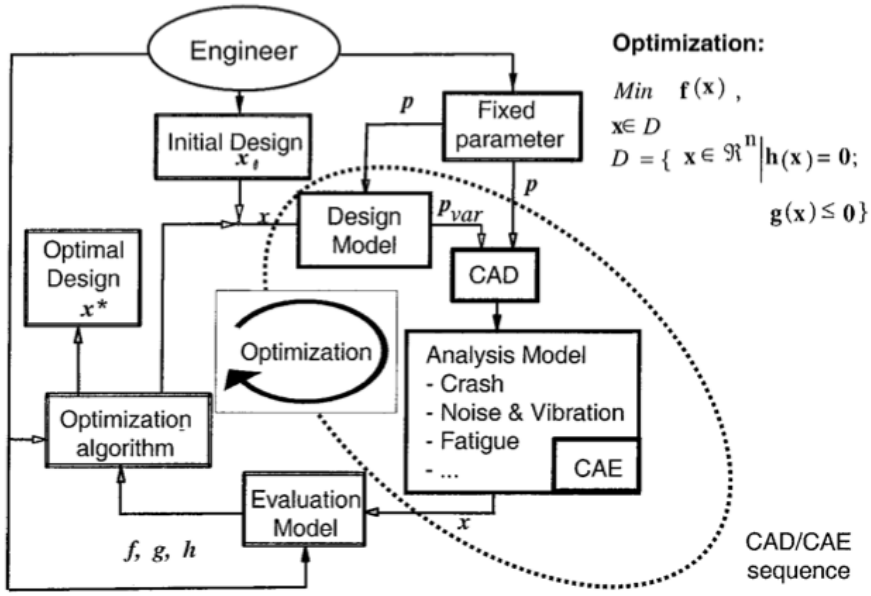

Figure 8: CAD, CAE, and optimization workflow. From Merkel, M., Schumacher, A. (2003).

A least square fit response surface is created with the design variables as inputs and damage and mass as the outputs. The details of the DOE used to generate the response surface model are not specified. The LMS/Optimus multi-objective optimizer is not specified but the optimizer used does provide a set of Pareto-optimal design solutions as shown in Figure 9.

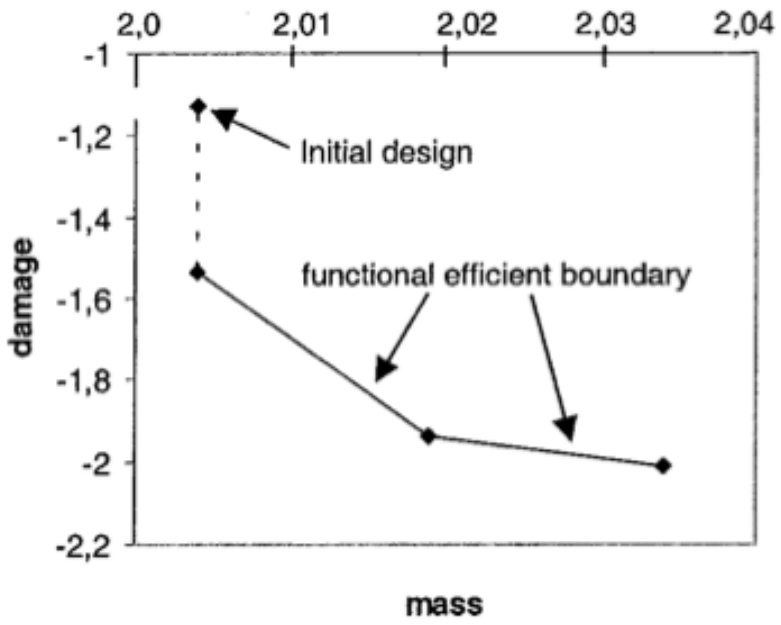

Figure 9: Results of multi-objective optimization. (From Merkel, M., Schumacher, A. (2003)).

In Merkel, M., Schumacher, A. (2003) UniGraphics, a commercial CAD system, coupled with MSC and LMS software which are commercial FEA, fatigue, and optimization software, are coupled to create an optimized vehicle steering knuckle. This method uses parameterized CAD and multi-objective optimization techniques as the framework presented in this thesis does. This method does not use CFD based modeling to calculate the various designs' performance. Further, the framework presented in this thesis only uses a response surface model when the CFD model requires more than a user specified time limit to calculate whereas the method presented in Merkel, M.,

Schumacher, A. (2003) always uses a response surface model to perform the optimization on. If the optimizer can optimize on the physics-based model rather than the response surface model, the optimized results do not need to be verified with a final physics based model run. Further, Merkel, M., Schumacher, A. (2003) do not utilize a second level optimization algorithm to aid the engineer in selecting the optimum design solution, from the Pareto-optimal design solution set as the method in this thesis does.

In Xu, B., Chen, N. (2009), a method is presented to use CAD, FEA, and multi-objective optimization algorithms to develop an optimized design of a manipulator of a cherry picker as shown in Figure 10.

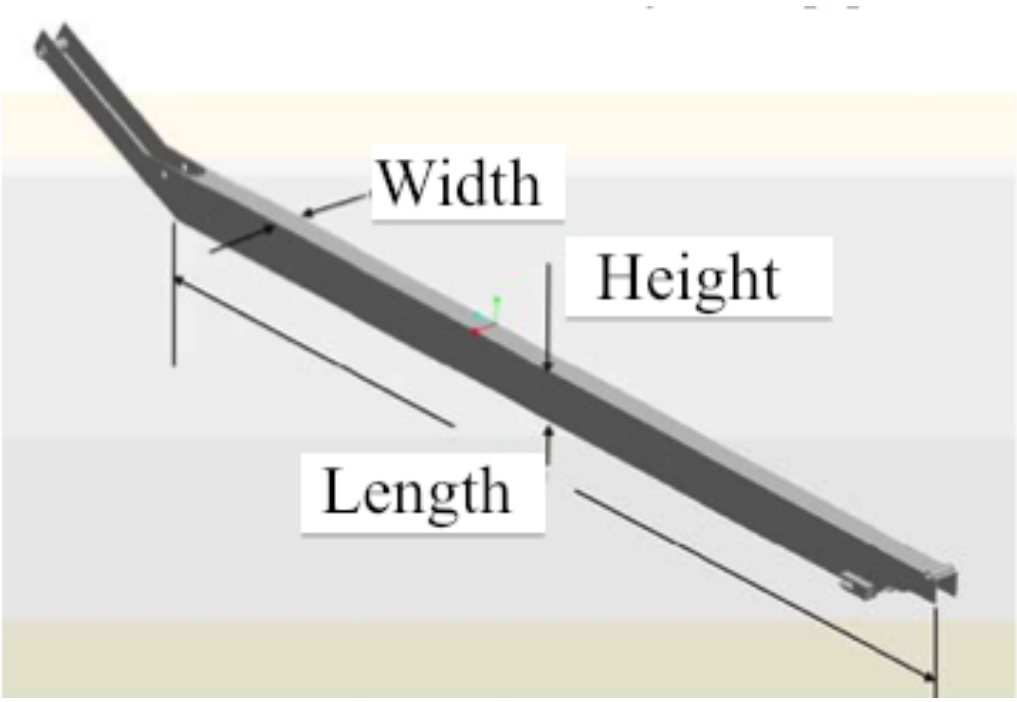

Figure 10: Geometry of manipulator. Xu, B., Chen, N. (2009).

In this work, Pro/ENGINEER is the CAD software, ANSYS® is the FEA software, and Isight is the optimizer and simulation workflow software. The simulation

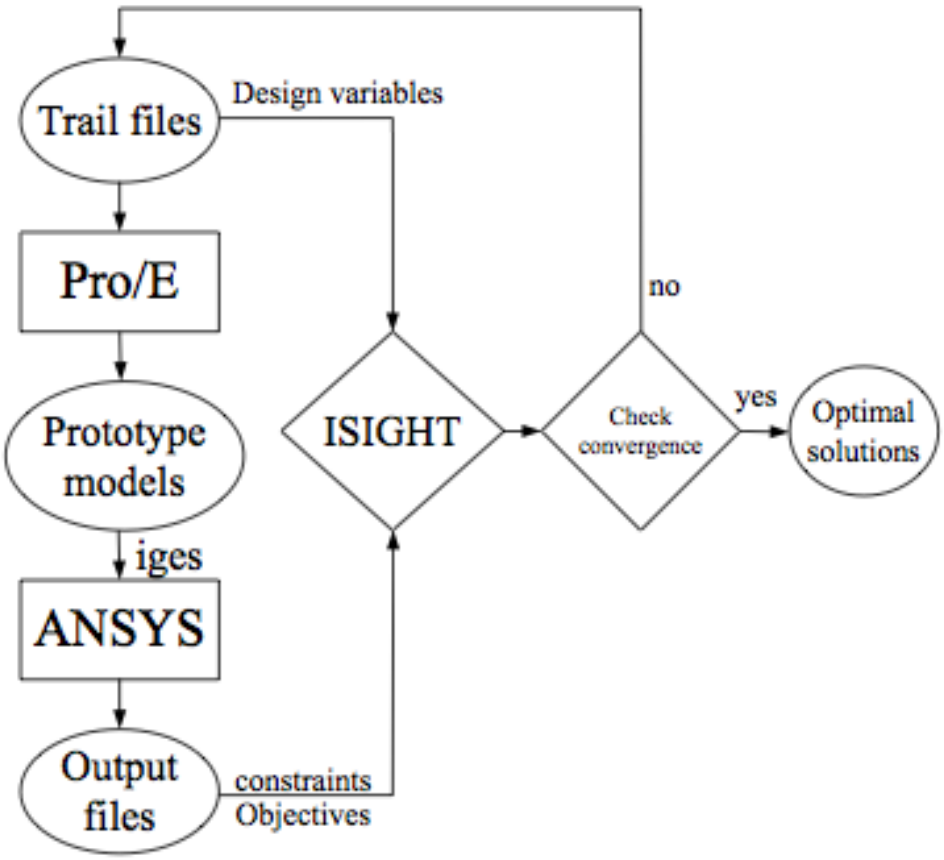

Figure 11: Simulation workflow for manipulator optimization. Xu, B., Chen, N. (2009).

workflow is shown in Figure 11.

The multi-objective optimization problem has the objectives to minimize the volume and maximize the length of the manipulator subject to an inequality constraint where the maximum equivalent stress in the manipulator be less than or equal to a

specified value. The method presented in Xu, B., Chen, N. (2009) couples nonlinear programming by quadratic approximation of the Lagrangian (NLPQL) with multi-island genetic algorithm (MIGA) to generate a Pareto-optimal set of manipulator arm design solutions.

The method presented in Xu, B., Chen, N. (2009) uses parameterized CAD and multi-objective optimization techniques as the framework presented in this thesis does. This method does not use CFD based modeling to calculate the various designs' performance as this thesis does. Further the framework presented in this thesis has the flexibility built in to allow the multi-objective optimizer to use a response surface model when the CFD model requires more than a user specified time limit to calculate or allow the multi-objective optimizer to optimize directly on the CFD model, whereas the method presented in Xu, B., Chen, N. (2009) does not have the flexibility to allow the multi-objective optimizer to use a response surface model. The response surface model offers the advantage of reducing the total time to arrive at a Pareto-optimal set of design solutions. Further the method presented in Xu, B., Chen, N. (2009) does not utilize a second level optimization algorithm to aid the engineer in selecting the optimum design solution, from the Pareto-optimal design solution set.

In Goto, A., Nohmi, M., Sakurai, T., Sogawa, Y. (2002) a CAD system has been developed for the optimization of hydrodynamic parts of pumps including impellers, bowl diffusers, volutes, and vaned return channels. This method uses 3-D CAD software, semi-automatic grid generation software, CFD analysis software, and a 3-D inverse design method. This method uses the 3-D inverse design method presented by Zangeneh,

M. (1991). Using the 3-D inverse design method, the blades are represented by sheets of vorticity, whose strength is determined by a specified distribution of bound circulation as shown in Equation 4 where V_θ is the circumferentially averaged swirl velocity.

$$\Gamma = 2\pi r V_\theta$$

Equation 4: Bound circulation.

Figure 12 shows the overall design system presented. The design system consists of a "blade design system" for designing blades or vanes of impellers/diffusers and a "channel design system" for designing the 3-D flow passage such as a volute casing and a vaned return channel.

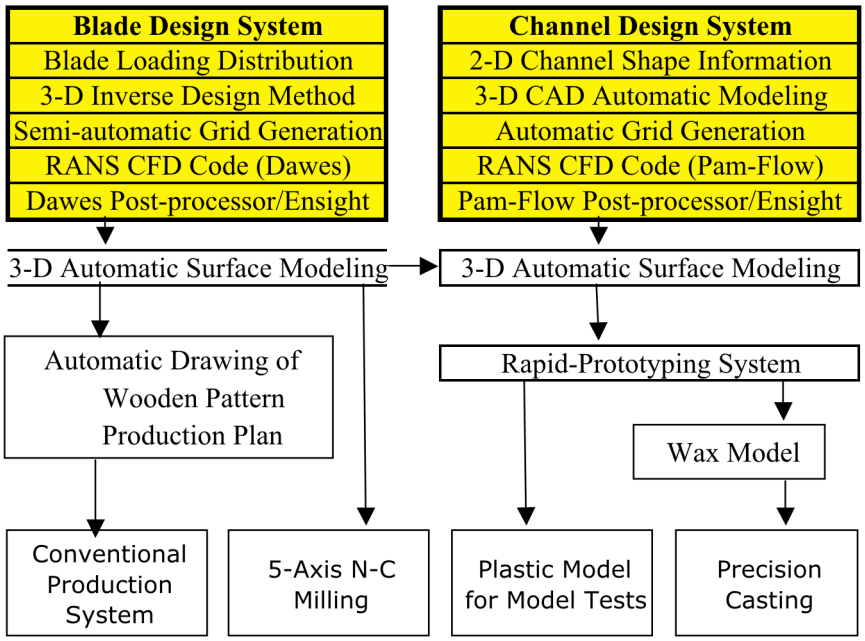

Figure 12: Pump design systems. (From Goto, A., Nohmi, M., Sakurai, T., Sogawa, Y. (2002)).

The blade design system starts from the meridional shape of impellers/diffusers using a database. Then the blades are designed to a specified circulation distribution using the 3-D inverse design method presented by Zangeneh, M. (1991). Next, the CFD grid is generated using a semi-automatic H-type grid. Finally, the fluid flow field within the impellers/diffusers are calculated by solving the Reynolds Averaged Navier-Stokes (N-S) equations by a Dawes N-S solver as presented in Walker, P. J., Dawes, W. N. (1990). For diffuser blades, a stage version of the Dawes code presented in Goto, A.

(1995) is used. A Dawes postprocessor and EnSight are used to visualize the 3-Dimensional flow field calculation results.

The channel design system starts with a 2-Dimensional representation of the major design variables of the volute cross-sections. Next, a 3-Dimensional representation of the volute is generated from the 2-Dimensional representations with a customized CAD system. Next, the CFD grid is generated fully automatically using the advanced front method as presented in Lohner, R. (1987 (1)). Finally, the 3-Dimensional N-S solver presented in Lohner, R. (1987 (2)) is used to solve the 3-dimensional flow field.

The use of the design systems presented in Goto, A., Nohmi, M., Sakurai, T., Sogawa, Y. (2002) allows for the systematic design of impeller/diffuser blades and channels. These systems are coupled with various rapid prototyping systems to validate the proposed optimum design solutions. The method presented in Goto, A., Nohmi, M., Sakurai, T., Sogawa, Y. (2002) uses very specialized CAD and CFD systems to achieve the optimized design solutions. Further the method is limited to the design of turbo machinery and is not suitable in its current form for general purpose internal flow component design optimization. The method also is not multi-objective in the sense that multiple conflicting objectives are being evaluated with the end result of a Pareto-optimum set of design solutions that allows the engineer to use higher-level information to choose the most optimum design solution. The framework presented in this thesis is applicable to general purpose internal flow components, uses commercial CAD and CFD software, and combines multi-objective and multi-level optimization.

Fuligno, L., Micheli, D., Poloni, C. (2006) and further described in Fuligno, L., Micheli, D., Poloni, C. (2009) present a method for optimizing the combustors of small gas turbines. The workflow uses a 0-Dimensional code to determine a baseline combustor design, CAD software to generate a parameterized axi-symmetric model of the combustor, CFD software to calculate the N-S equations including combustion, and simulation workflow and optimization software to manage the simulation. CATIAv5 is the CAD software, icemCFD is the CFD meshing software, CFX™ is the CFD software, and modeFRONTIER is the simulation workflow and optimization software used. Nash's game theory algorithm is used as the multi-objective optimization algorithm.

The design variables are the position and size of the liner hole arrays, the total area of the liner hole arrays, and the shape of the exit duct. The objectives of the optimization are to minimize NO_x emissions, pressure losses, and the combustor exit pattern factor. The results of the test case are shown in Figure 13.

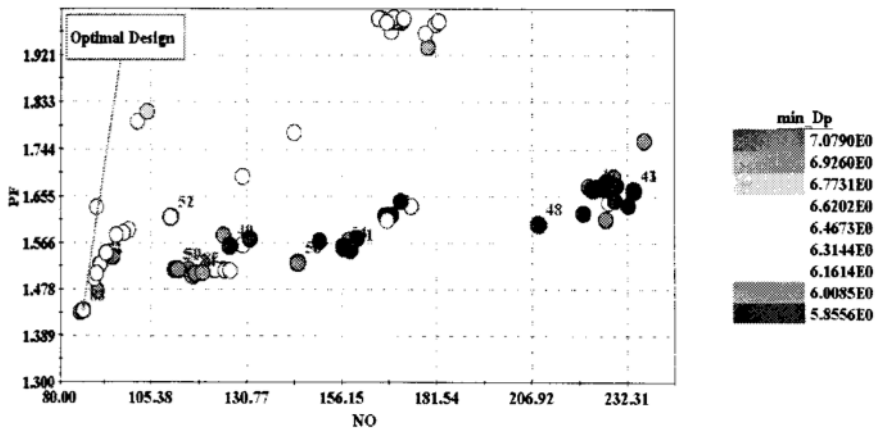

Figure 13: Different configurations computed by the optimizer in the objective space, with the chosen optimum solution as indicated. (From Fuligno, L., Micheli, D., Poloni, C. (2006)).

The method presented in Fuligno, L., Micheli, D., Poloni, C. (2006) uses commercial software and is restricted to small CFD models as demonstrated on small gas turbines. A multi-objective optimization algorithm is used to generate a set of Pareto-optimum design solutions, but this method does nothing with the Pareto-optimum design solutions other than choose a single solution that is at the minimum of the conflicting objectives. The method does not make use of a second level optimization algorithm that assists the engineer in determining what the optimum design solution should be. It seems possible that rather than using a multi-objective optimization algorithm, the multiple objectives could be cast into a single objective with appropriate weighting and scaling to arrive at the optimal solution. Finally this method is limited to 100 simulation runs due to the compute time of the CFD domain.

The framework presented in this thesis uses commercial software and is a general purpose framework. The use of a response surface model allows the method presented in this thesis to be applied to larger CFD computational domains, which are characterized by increased computational time, without significant increases in the time to generate Pareto-optimal design solutions. Further, the framework presented in this thesis uses a second level optimization algorithm that searches the Pareto-optimal design solution set at the users direction to aid the engineer in determining which design solution is the optimum design solution.

Tahara, Y., Tohyama, S., Katsui, T. (2006) present a method for using multi-objective optimization and CFD in ship design. The CAD software used is NAPA, which is the leading CAD software in ship design. The CFD solver used is FLOWPACK, which was developed by Tahara, Y., Hayashi, G. (2003), Tahara, Y., Katsui, T., Himeno, Y. (2004), and Tahara, Y., Wilson, R., Carrica, P. (2005). The simulation workflow and optimization software used was developed by Tahara, Y., Sugimoto, S., Murayama, S., Katsui, T., Himeno, Y. (2003). A multi-objective genetic algorithm (MOGA) was used in conjunction with a sequential quadratic programming (SQP) where the SQP algorithm was used to validate the optimum found with the MOGA algorithm. The MOGA is used to generate a Pareto-optimal set that has minimized the delivered horsepower and first overshoot angle at 10/10-degree-Zigzag. The SQP is then used to optimize each objective separately to verity that the Pareto-optimal set is accurate.

The method presented in Tahara, Y., Tohyama, S., Katsui, T. (2006) is very specialized for the ship hull design optimization. The CAD software used is widely used

in the ship building industry, but is not widely used as a general purpose CAD software. The CFD software is not general purpose and has been developed by the authors of the method. The simulation workflow and optimization algorithms used are general purpose, but are implemented in a non-general framework. The method does not make use of a response surface model to reduce the computational time, which was 100 hours for one optimization run.

The method presented in this thesis provides a general framework that uses multi-objective optimization to facilitate engineering decisions in the PDP of internal flow fluid/thermal components.

Kipouros, T., Jaeggi, D., Dawes, B., Parks, G., Savill, M. (2005) present a multi-objective method for optimizing the overall performance of turbo machinery blades. The multi-objective integrated design system used in the work has been developed and described by Kipouros, T., Parks, G. T., Savill, A. M., Jaeggi, D. M. (2004) building on the single- objective integrated design optimization system (BOS3D) developed by Harvey, S. A. (2002) and described by Dawes, W. N., Kellar, W. P., Harvey, S. A., Dhanasekaran, P. C., Savill, A. M., Cant, R. S. (2003). The system combines an existing, efficient and flexible geometry parameterization scheme, a well-established CFD package and a novel multi-objective variant of the Tabu Search (TS) optimization algorithm for continuous problems (Jaeggi, D. M., Asselin-Miller, C. S., Parks, G. T., Kipouros, T., Bell, T., Clarkson, P. J. 2004). Two test cases of this method show that multi-objective optimization found designs of turbo machinery blades that matched or exceeded performance of the blades optimized with earlier single-objective studies.

This work uses the integrated design system of unique CAD and CFD software coupled with a modified TS optimization algorithm. The CFD mesh used in these analyses is a fully structured grid.

Again, the method presented in this thesis provides a general framework that uses multi-objective optimization to facilitate engineering decisions in the PDP.

Micheli, D., Pediroda, V., Pieri, S. (2008) presents a method where CATIA, icemCFD, and ANSYS® CFX™ are integrated with modeFRONTIER to optimize the recuperator of a microturbine. This method uses the MOGA to generate Pareto-optimal design solutions to minimize the pressure drop through the recuperator and minimize the total surface area of the recuperator. The work demonstrates that this technique is successful at generating the Pareto-optimal set, but there is nothing presented regarding how to select the optimal design solution from the Pareto-optimal set.

The method presented in this thesis uses a second level optimization algorithm to aid the engineer in choosing the optimum design solution from the Pareto-optimal design solution set.

Multi-level optimization methods were initially developed in the 1960's with the goal to facilitate the optimization of large-scale systems in industrial processes and to solve trajectory prediction problems (Bauman, E. J. (1971), Schoeffler, J. D. (1971), Wismer, D. A. (1971), Leondes, C. T. (1968)). Three level programming is a class of multi-level optimization where there are three independent decision makers with each decision maker attempting to optimize its objective function with affects of each of the other decision makers accounted for (Anandalingam G., Apprey V. (1991), Shi X., Xia

H. (1997), Wen U. P., Bialas W. P. (1986), Osman M. S., Abo-Sinna M. A., Amer A. H., Emam O. E. (2004)). Multi-level optimization methods have been applied in operations management (Roghanian E., Sadjadi S. J., Aryanezhad M. B. 2007) and resource distribution (Cassidy R., Kirby M., Raike W. 1971).

This class of applications of multi-level optimization in the literature have had limited application in engineering decision circumstances. In many cases the problems solved have been theoretical in nature. There has also been limited use of multi-level optimization in connecting business and engineering organizations. The method used in this thesis connects the engineering activity of multi-objective optimization to the higher-level organization so that decisions can be made in the presence of Pareto-optimal design solutions with higher-level organizational information. This assures that the design solution chosen during the Level-2 optimization is optimum.

Multi-level optimization has been applied to multi-leveled engineered systems such as micro-electro-mechanical systems (MEMS), (Farnsworth M., Benkhelifa E., Tiwari A., Zhu M. 2010), spacecraft design (Lavagna M., Finzi A. E. 2002), shape optimization in metal forming (Thiyagarajan N., Grandhi R. V. 2005), aircraft wing design (Gantois K., Morris A. J. 2004), and gas turbine blade design (Akmandor I. S., Oksuz O. 2010).

In Farnsworth M., Benkhelifa E., Tiwari A., Zhu M. (2010) a multi-level optimization method is used to develop a MEMS device. MEMS are a field that has evolved out of the integrated circuit industry, which uses assembly techniques from the field of Very-Large-Scale-Integration (VLSI) (Fujita, H. (2007), Benkhelifa, E.,

Farnsworth, M., Tiwari, A., Bandi, G., Zhu., M. (2010)). The method presented in Farnsworth M., Benkhelifa E., Tiwari A., Zhu M. (2010) applies multi-level optimization to the hierarchal design of MEMS devices at the system, device, physical, and process levels.

This method is applied in a different field of engineered components than the method presented in this thesis. MEMS devices are a system in and of themselves, whereas the method presented in this thesis is applied at the component level and the multi-level optimization in this thesis is applied to engineering decisions, rather than physical system levels.

In Lavagna M., Finzi A. E. (2002) a multi-criteria decision making approach and fuzzy logic theory are used to automate the preliminary design of a spacecraft. A spacecraft is a large system composed of many interdependent sub-systems, which makes the design of a spacecraft an excellent candidate for the use of multi-objective, multi-level optimization. The method in Lavagna M., Finzi A. E. (2002) is used to develop preliminary spacecraft designs. In some cases a new sub-system is designed, while in most cases existing sub-systems are integrated together to form the overall spacecraft system. Fuzzy logic is used to simulate human interaction with the preliminary design of the spacecraft. Overall the method is used for choosing a preliminary spacecraft design, not the detailed design of the sub-systems and components that makeup the spacecraft.

In this thesis, the multi-objective and multi-level optimization are used to facilitate the detailed design of components. The engineer is actively involved in the second level optimization activity rather than simulated with fuzzy logic. Again, the

work presented in Lavagna M., Finzi A. E. (2002) is a different field of engineered components and a different application of multi-level optimization.

In Thiyagarajan N., Grandhi R. V. (2005), a multi-level approach is presented to determine the optimum starting shape for a forging billet. The method uses basis functions to represent the starting billet shape combined with response surface modeling to calculate the outputs of the forging process associated with the input parameters. The initial shape is chosen from a taxonomy of shapes. Physics based models of the forging process are used to generate the response surface model which is used to evaluate the billet shape (design variables) at meeting the objective of minimizing strain variance subject to the constraint of not under filling the forging die. The multi-level aspect of the method is to modify the basis functions to generate new starting billet shapes.

The method presented in Thiyagarajan N., Grandhi R. V. (2005) is a single objective optimization problem with one constraint. The multi-level aspect of the method could be viewed as a second level of a single objective optimization problem. The method used in this thesis utilizes multi-objective optimization techniques to generate the starting optimum design solutions rather than a taxonomy of starting design solutions. Further the method in this thesis uses the second level optimization to aid the engineer in determining the optimum design solution. Again, the methods in Thiyagarajan N., Grandhi R. V. (2005) are for a different class of problems and do not utilize multi-level optimization as the method presented in this thesis does.

The method presented in Gantois K., Morris A. J. (2004) is used to design a large scale civil aircraft wing while accounting for manufacturing costs using a multi-

disciplinary optimization approach. The method involves various companies using different engineering methods and software and cost management methods. The design problem has the single objective of designing a wing with the minimum direct operating costs. The engineering parameters that impact the wing design were included through a series of reduced order models that were derived from physics based models. As various contributing companies developed their pieces of the reduced order model there was a central database structure that managed the flow of information.

The method presented in Gantois K., Morris A. J. (2004) is a single objective optimization activity that involves development of a sub-system of an aircraft within a disparate multi-disciplinary organization. This method was developed for a different class of problems and does not utilize multi-level optimization to facilitate engineering decision making as the method presented in this thesis does.

In Akmandor I. S., Oksuz O. (2010) a method is developed to optimize the aerodynamic characteristics of axial turbine blades. The method makes use of a Multi-Objective Genetic Algorithm (MOGA) (Osyczka, A., Kundu, S. 1995, Osyczka, A. 2002) that has been modified to use two levels of fidelity when calculating the blade objectives. The method uses parameterized blade designs composed of six 2-Dimensional layers stacked to form the blade 3-Dimensional representation as shown in Figure 14.

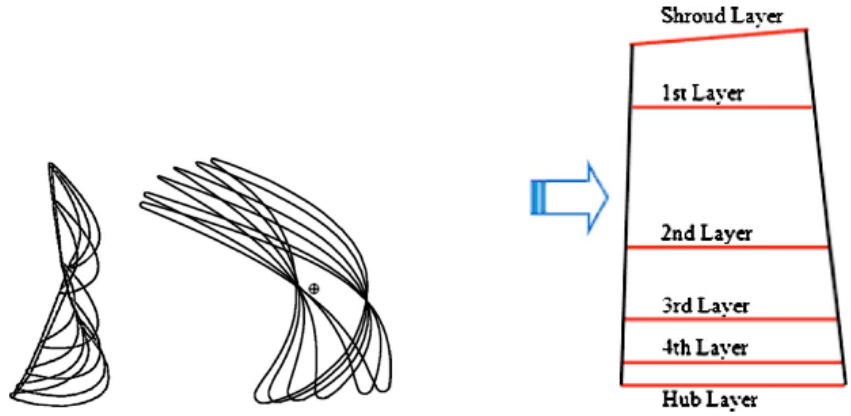

Figure 14: Parameterized blade. (From Akmandor I. S., Oksuz O. (2010)).

The design variables for the study are the blade inlet and exit angles, leading and trailing edge wedge angles, stagger angle, circumferential rotation angle, and the number of blades. The objectives of the multi-objective optimization are to maximize the adiabatic efficiency and maximize the torque. ANSYS® Turbo Grid, and ANSYS® CFX™ are used as the mesh generation software and CFD solver in the method.

The method presented in Akmandor I. S., Oksuz O. (2010) makes use of commercial mesh generation software and a general purpose CFD solver to solve the axial flow turbine blade design problem. The multi-level aspect to the method is the use of a low and high fidelity CFD model. In this thesis the framework is developed and demonstrated on three different design problems and the second level-optimization algorithm is developed to aid the engineer in the decision process of choosing the optimum design solution.

Based on the review of the pertinent literature the following gaps are identified for the Level-1 optimization:

1. Limited use of response surface models used in the literature
2. Simulation workflows are not general purpose
3. Current methods are not multi-level to facilitate engineering decision making
4. Wide use of weighted sum single-objective optimization techniques rather than multi-objective optimization techniques

This thesis addresses gaps 1-3 identified in the Level-1 optimization methods in the literature. Gap 1 is a gap because often times CFD models will require calculation time measured in hours or day, not minutes. Multi-objective optimization techniques often require thousands of objective function evaluations, which would be CFD runs. Through the use of a response surface model larger CFD models can now be candidates for the use of multi-objective optimization to facilitate component design early in the PDP.

Gap 2 is a gap because the methods in the literature are for one design problem, i.e. The optimum design of a manipulator, the optimum design of a steering knuckle, the optimum design of a axial turbine blade, etc. The framework presented in this thesis is applicable to internal flow design problems that can be parameterized in Pro/ENGINEER® and where the medium is an ideal, incompressible gas and the flow is turbulent. This thesis demonstrates the use of the developed framework on three different test cases with different geometry, design variables, and objectives.

Gap 3 is a gap because the methods in the literature stop after the Pareto-optimal design solution set is created. These methods don't assist the engineer in determining which design solution from the Pareto-optimal set is the optimum design solution. The Level-2 optimization in this thesis searches the Pareto-optimal set of design solutions with the user evaluating each design's optimality against higher-level information.

Based on the review of the pertinent literature the following gaps are identified for the Level-2 optimization:

1. Limited application of multi-level optimization to engineering decision science
2. Limited use of multi-level optimization for connecting organizational and engineering levels of information
3. Limited application to general thermal/fluid design problems

This thesis addresses gaps 2 and 3 of the multi-level optimization methods. Gap 2 is a gap because design problems are characterized by having multiple solutions to the problem. The implication of this is that there are multiple acceptable solutions but there are few optimum solutions. It is the design engineer's chief aim to find the most optimum solution to the design problem at hand. By developing a second level optimization algorithm that assists the engineer in choosing the optimum design solution from the Pareto-optimal design solution set the engineer is assured to be selecting the most optimum design solution to the design problem as the problem was decomposed in the multi-objective optimizer.

Gap 3 is a gap because in the last decade CAE software has become easier to use and computer power has increased such that CAE software is more widely used in the PDP. In parallel, in the last decade there has been a desire to further reduce product development times and resource consumption. To achieve this next step in reduction of product development time and resource consumption the need for increased integration of CAE software earlier in the PDP is needed. This will provide the design engineer with increased design problem knowledge earlier in the PDP, which is when this increased knowledge is most valuable in the PDP timeline and can impact the product design the most. To achieve this, the Level-2 optimization framework presented in this thesis was developed.

CHAPTER 2 : PRODUCT DEVELOPMENT PROCESS

This chapter presents four of the common product development processes that are widely used in various industries to develop and introduce new products to the market. This chapter illustrates that if CAE software is going to be used to facilitate product design, it must be integrated earlier into the PDP. The framework developed in this thesis allows CFD to be used earlier in the PDP by coupling multi-objective optimization with CFD.

From the water pail with a handle to a passenger aircraft, humans have been designing products and services for thousands of years. Both the water pail and the passenger aircraft are the end result of some sort of PDP. The water pail is rather simple when compared to the passenger aircraft, which shows that the design process for each device will have vastly different tasks and techniques that result in the successful product.

Ullman, D. G. (1997) defines the design process as the organization and management of people, and the information they develop in the evolution of a product. The literature generally uses product design and product development in the same context. The remainder of this thesis will use PDP to refer to the definition offered by Ullman, D. G. (1997). If we contemplate the design of a water pail with a handle, one

can see that it seems reasonable that a single person could manage the PDP for the device. One person could assess customer needs, understand the market for the water pail, have sufficient materials knowledge to specify appropriate materials, provide a detailed design, and manage the supply chain for the water pail. If we contemplate the development of a passenger aircraft, it is clear that the development process requires many different people with various expertise working together to deliver a successful passenger aircraft. The common thread in the development of the water pail and the development of the passenger aircraft is the presence of a PDP. Regardless of the complexity of the product being developed, a process is required to develop the product efficiently. Ulrich, K. T. and Eppinger, S. D. (2003) offers the details of five different products and the development efforts associated with each as shown in Table 4.

Table 4 Details of five different products and the development efforts associated with each. (Adapted from Ulrich, K. T. and Eppinger, S. D. (2003)).

		Stanley Tools Jobmaster Screwdriver	Rollerblade In-Line Skate	Hewlett-Packard DeskJet Printer	Volkswagen New Beetle Automobile	Boeing 777 Airplane
Annual Production Volume	Units/Year	100,000	100,000	4,000,000	100,000	50
Sales Lifetime	Years	40	3	2	6	30
Sales Price	$	$3	$200	$300	$17,000	$130 Million
Number of Unique Parts (part numbers)	Parts	3	35	200	10,000	130,000
Development Time	Years	1	2	1.5	3.5	4.5
Internal Development Team (Peak Size)	People	3	5	100	800	6,800
External Development Team (Peak Size)	People	3	10	75	800	10,000
Development Cost	$	$150,000	$750,000	$50 Million	$400 Million	$3 Billion
Production Investment	$	$150,000	$1 Million	$25 Million	$500 Million	$3 Billion

Regardless of the product being developed the goal in product development, in the for profit market, is to produce a product that meets customer expectations, is delivered to the market in the shortest amount of time, exhibits high quality, and provides sufficient return on investment for the company shareholders.

Before the process of generating a detailed design of a product is discussed, it is best to understand the various steps that exist in the PDP. Most of the products a person interacts with on a regular basis have been developed through some sort of PDP. According to Rosenthal, S. R. (1992), during the development of a product it will pass through various forms of the product design. Figure 15 shows these forms of the product

design and their associated description. In general, in this thesis product development refers to the process by which a new product is developed, and a product design as the details that embody the product. Figure 15 shows that during the PDP the product design will have various forms, or levels of detail that describe the overall product. Early in the PDP the design can be as simple as a sketch or artists rendering. As the product design moves through the various steps of the PDP, the product design will become detailed. As a product design passes through these various forms many decision must be made. These design decisions are made as various trade-offs are evaluated. If we consider the water pail with the handle, the trade-offs of a water pail with or without a handle could be evaluated, or a material choice of galvanized steel vs. injection molded polypropylene could be evaluated. In the passenger aircraft example trade-off decisions are also made, but the implication is that as the system complexity increases the trade-off decisions effect is more wide spread through the various departments involved in the PDP.

Form	Description
Concept Paper	Preliminary qualitative description of intended product.
Sketch	Rough drawing of a product or component.
Blueprint	Precise drawing of a product or component.
Physical Model	3-Dimensional representation of shape and exterior appearance of product.
Simulation Model	Programmed representation of product layout or functions.
CAD File	Electronic representation of parts/product geometry.
Design Release Bulletin	Full description of product for use in designing the manufacturing process.
Bill of Materials	Precise list of all parts of the end product.
Process Plan	Detailed description of how product is to be manufactured.
Service Plan	Description of field service requirements (such as replacement parts, service delivery standards, technical support procedures, test equipment).

Figure 15 Forms of product design as the product is developed. (Adapted from Rosenthal, S. R. (1992)).

Today, various forms of the PDPs exist to help deliver a new product to the market faster, that meets the customer needs with high product quality. The PDP takes on various forms, but generally there is a stage and gate system that describes the process. Each stage of the PDP is where various activities occur as they relate to product development. As an example, in the detailed engineering design stage of the PDP the details of the new product design are worked to completion. All of the details of how the product must perform, what the product will look like, how the product will be manufactured among other details are determined in this phase. Also, during this phase

CAD electronic models are widely used to describe the product design. CAE models are used to determine the details of the design of the product to meet performance requirements. Also Computer Aided Manufacturing (CAM) can also be implemented during this phase to build early prototype parts of a given design. With all of this activity there needs to be a point where the program management team needs to evaluate the work completed and determine if the new product is ready to move to the next stage. This is generally referred to the gate, which is located between two new PDP stages. The gate that follows the detailed engineering design stage described above is the design release gate. At this gate the program management team will seek to verify that the new product meets all of the specifications, has an appropriate return on investment, and that the design can be manufactured. At the exit of this gate, the new product design is released for prototype production and product design validation.

Various forms of this stage and gate PDP are discussed in the literature. Following is a review of some of the new product development processes.

Cooper, R. G. (1990) offers what is referred to as a stage gate system that has five stages and 5 gates with an idea phase before Gate 1 and a post implementation review activity after Gate 5. The stage gate system is defined as a conceptual and operational model for moving new products from idea to product launch. Figure 16 shows an overview of the stage gate system presented by Cooper, R. G. (1990).

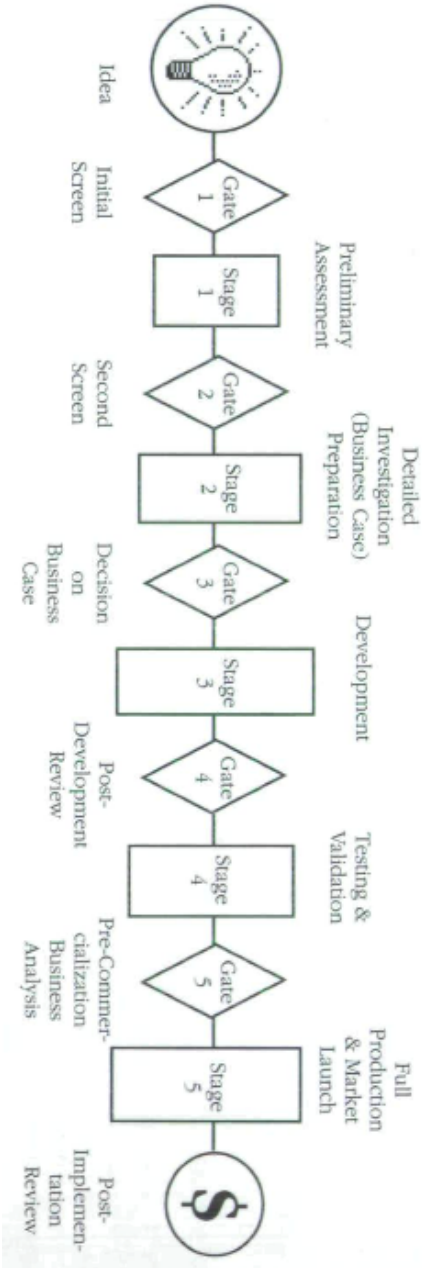

Figure 16 Overview of a stage gate system. (From Cooper, R. G. (1990)).

In Cooper's stage gate system the PDP is initiated with an idea, which must pass

through Gate 1. Gate 1 is called the "Initial Screen" and is the first gate in the stage gate system and is the first decision to commit resources to the new product idea. Gate 1 subjects the product idea to a list of "must meet" and "should meet" product criteria. Generally these criteria address product strategic alignment, project feasibility, and market opportunity. Passing through Gate 1 indicates that there is a tentative commitment to developing the new product idea and the new product idea then moves into Stage 1.

During Stage 1 which is called the "Preliminary Assessment" the product idea technical and market qualities are evaluated in a preliminary manner. Some of the marketing activities might include a literature review, reviews with potential strategic customers, and focus group reviews with a proof of concept of the new product idea. In parallel an assessment of the technical feasibility of the product idea is conducted. The technical feasibility assessment generally evaluates the product development feasibility, manufacturing feasibility, and product costs associated with the product idea. Generally the incurred costs during Stage 1 are low and the time in this stage is relatively short.

Gate 2 which is called the "Second Screen" is a repeat of Gate 1 with the new information that was gathered during Stage 1. The list of "must meet" and "should meet" criteria are evaluated again with the potential for additional items added to these lists based on market knowledge gained from Stage 1. The economics of the new product idea are assessed at this gate in a simple fashion, which may include the calculation of the payback period for the new product idea.

After the new product idea passes Gate 2 it enters Stage 2 which is called "Definition", which is the final stage before product development activities are started. During this stage rigorous market research is performed to determine the customer's needs, wants, and preferences are as they relate to the new product idea. Potential customers may be asked to perform concept testing to help identify what the potential customer acceptance of the new product idea will be. Competitive studies of similar products may also be performed. At this stage it is important that the customer base be well understood so that the product that is developed in the end is acceptable to the customer. A detailed technical feasibility study is also completed during Stage 2. All of the customer needs, wants, and preferences are translated into a type of specification for the product. It is important that the specifications that are developed are feasible with appropriate product and manufacturing technology available and that the economics of developing the new product idea are feasible. There may be some preliminary product design and testing that occurs to move the new product idea through this stage, but the work is normally proof of concept design types and testing. Finally, a refined financial analysis is completed of the new product idea. This analysis is of importance for passing Gate 3, because once the product idea is past Gate 3 significant investment is made to develop the new product idea.

Gate 3 which is called the "Decision on Business Case" is the final gate before the development stage of the stage gate system described by Cooper, R. G. (1990). This is the last point where the development of the new product idea can be stopped before significant investment is made in the new product idea. The list of "must meet" and

"should meet" criteria evaluated in Gate 2 are evaluated again at Gate 3. All of the activities that were conducted in Stage 2 are reviewed to understand if the activities were completed properly and that the results were positive for the development of the new product idea. Because the exit of Gate 3 begins the commitment of financial resources to the project, a review of the financial analysis completed in Stage 2 must be successfully completed before the exit of Gate 3. Before the product program can move past Gate 3 the program definition must be complete and agreed to by all stakeholders. This is of prime importance because this determines what development activities need to occur in Stage 3. Things like the market definition, position in the market, product specifications, and manufacturing details are reviewed and approved before the new product idea moves to Stage 3.

At Stage 3 which is called "Development", the new product idea is developed into the details required to fully embody the new product idea. At this stage the CAD, CAE, and CAM tools are used in full-force to develop the new product idea into a detailed product. At this stage detailed product verification, marketing, and operations plans are developed and the financial analysis of the product is updated. Any legal, patent, and or copyright issues that arise during this stage are resolved before moving to Gate 4.

Gate 4 which is called the "Post-Development Review" is a check of the progress of the development of the new product. The activities completed in Stage 3 are reviewed to ensure that the execution was done correctly and that the results continue to be positive toward meeting the new product specifications. As the new product is developed more detailed information becomes available regarding the financial commitments required for

the new product. The financial analysis of the new product is updated and reviewed at Gate 4 to ensure that the product is still financially positive. The detailed marketing and operations plans are reviewed with the expectation that the plans will be executed.

Stage 4 which is the "Validation" stage, is where the product design is tested to validate that the product design meets the specifications agreed to in Gate 3. At this stage, the product itself is tested, the production processes are verified, customer acceptance is verified, and the financial aspects of the product are verified. Activities including laboratory testing, field testing, customer acceptance testing, limited production, market introduction, and detailed financial analysis all occur during Stage 4. All of the details of the product must be verified and ready for commercialization at this point in the stage gate system.

Gate 5 which is called the "Pre-Commercialization Decision" gate, is the final gate before commercialization or production of the product occurs. This is the last opportunity to stop the project before production occurs. All of the activities that occurred in Stage 4 are reviewed to make certain that the results were positive to the new product and if the results were not positive a corrective action plan is put in place to address the issues. The final operations and marketing plan are reviewed and approved for implementation in Stage 5.

Stage 5 which is called the "Commercialization" stage, is where the production and marketing of the product are launched in full-force.

Finally a "Post-Implementation Review" of the new product development program and new product is performed. This is where the new product is no longer a

new product; rather it is another product in the company's product line. This is where the new product development program execution and the new product itself are reviewed to understand the weaknesses in the PDP and the product are. Detailed audits of revenue, costs, profits, timelines, and product performance are reviewed. This is the companies' opportunity to reflect on the successes and failures of the PDP and the product itself so that future product development processes and products can make necessary adjustments to avoid the failures and build on the successes of the previous development process and product.

In summary, Cooper, R. G. (1990) offers a 5 stage and 5 gate stage-gate system for developing new products. This system assumes that the new product idea exists a priori and that the post implementation review occurs after full production launch. The five gates and stages are as follows:

- Gate 1: Initial Screen
- Stage 1: Preliminary Assessment
- Gate 2: Second Screen
- Stage 2: Definition
- Gate 3: Decision on Business Case
- Stage 3: Development
- Gate 4: Post-Development Review
- Stage 4: Validation
- Gate 5: Pre-Commercialization Decision
- Stage 5: Commercialization

The simulation workflow developed in this thesis can be used from pre-Gate 1 to Gate 4 of the stage and gate system presented by Cooper, R. G. (1990). Specifically the simulation workflow focuses on how to use CFD to facilitate the trade-off decisions that are required during the first 3 stages of the PDP. Design knowledge that is gained early in the PDP is very valuable, because this knowledge can assist the organization in making more informed decisions.

Rosenthal, S. R. (1992) offers a process for managing the development of new products that is called the new product introduction process (NPI). The NPI process has 4 gates and 5 phases and is shown in Figure 17.

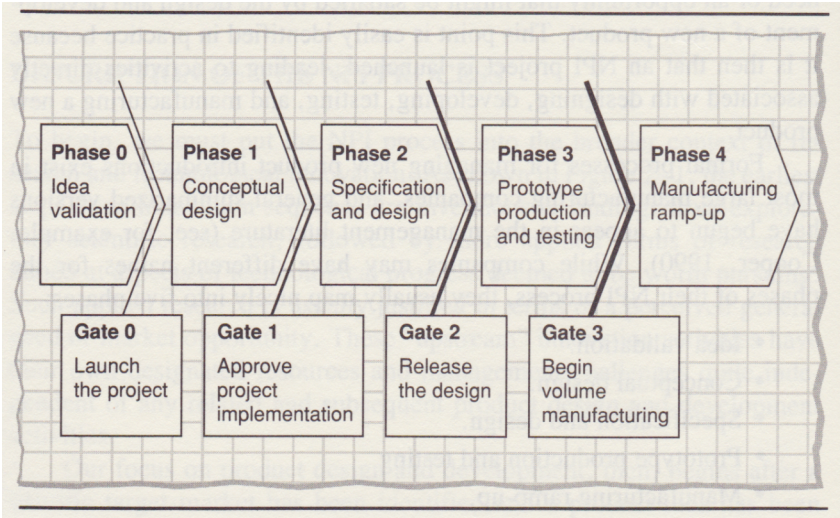

Figure 17 Overview of NPI phases and gates. (From Rosenthal, S. R. (1992)).

Phase 0, the "Idea Validation" phase consists of the new product idea identification, screening, and initial refinement. At this phase the case for the new

product idea is evaluated against the market and the proposed new product idea technical performance. Rosenthal, S. R. (1992) suggests the following considerations be evaluated at this phase:

- Identification and description of the target customer and an overview of the customers' needs that are not met in the market currently.
- An evaluation of the current technology that exists to develop the new product idea into a product that meets the customers needs.
- The market potential for the proposed new product idea.
- The existing competitive advantage of the company and anticipated change in competitive advantage by pursuing the introduction of the new product idea to the marketplace.
- An evaluation of the financial and human resources required to develop the new product idea.

Gate 0 follows Phase 0 and is referred to as the "Launch the Project" gate in the NPI process. This gate review usually consists of a detailed review to understand the required economic and technical feasibility of investing company resources in the proposed new product idea. Generally, at this gate sufficient market research and technical feasibility studies have been completed to understand how the new product idea would fit within the companies current product lineup and the market need for the proposed new product. A proposed NPI schedule, target cost, product risk, technical challenges associated with the product idea, and ability to develop the new product will also be reviewed at this gate. Rosenthal, S. R. (1992) places significant importance on

having executive management involved in the NPI process at Gate 0 because financial and human resources will be allocated to move the product idea to Phase 1.

Phase 1 is referred to as the "Conceptual Design" phase of the NPI process. At this phase of the NPI process the business feasibility of the new product idea is assessed. As part of this business feasibility a set of commercial specifications are identified which will guide the product design. Things like product aesthetics, performance, and price are established. Technology and manufacturing gaps are identified and the risk of these gaps is evaluated relative to the development of the new product idea. Marketing feasibility is evaluated relative to the company's business strategy which results in estimates of marketing and sales objectives, marketing methods, resource requirements, and a proposed product launch schedule. The output of this phase is a document that translates the market needs into a set of design or engineering specifications that will guide the rest of the NPI process.

Gate 1 is referred to as "Approve Project Implementation" and is where management reviews all aspects of the project plan accessing the likelihood of successfully achieving the goals set in Phase 0 and Phase 1 of the NPI process. The focus of this review is on the definition of the market and customer, the proposed business plan, and the feasibility of the project from the technology required, manufacturing, and marketing perspective. The design or engineering specifications developed in Phase 1 are reviewed in detail to verify that the customer requirements were translated into an engineering specification that is achievable within the time frame of the project, with appropriate technology, and is realizable with the manufacturing plan. Depending on the

type of company, management may review the timing and resource requirements of this new product program relative to others within the company to make sure that the company has sufficient resources to develop their full product portfolio and to understand any synergies that can be exploited between various new product programs. At the successful completion of Gate 1 the new product idea moves to Phase 2 with the appropriate resources allocated.

Phase 2 which is referred to as "Specification and Design" is the phase where the detailed product specifications and production process are refined to achieve the release of the new product design and manufacturing plan. This phase is at times appropriately called the engineering design phase. At this phase all of the engineering details that are required to meet the product specifications developed in Phase 1 are worked out. During this phase the CAD, CAE, and CAM tools are used in full-force to support the development of the new product. All of the stakeholders in the new product participate in this phase of the NPI process to make sure that the design that is delivered provides acceptable trade-offs between the various requirements. Of particular interest is the participation of manufacturing/process engineering at this phase of the NPI process. As the detailed designs are developed with manufacturing input the potential to design high manufacturing costs out of the new product design is the greatest. It is always easier to eliminate the costs before they become designed into the new product. The outputs of this phase are the detailed designs and bill of materials (BOM) that fully embody the new product idea into a tangible new product.

Gate 2 which is referred to as “Release the Design” is the gate where all of the work up to this point in the NPI process is reviewed with the positive outcome of a design that is released. Often there will be a prototype of the new design that is evaluated at this gate. The product design must demonstrate that it meets all engineering specifications, is manufacturable, is accepted in the market place, has met the target financial performance, and is on target according to the timeline for the new product. Any gaps (technical, market, cost, etc) that are identified must have a plan in place to address them before the design is released for Phase 3 of the NPI process.

Phase 3 which is referred to as “Prototype Production and Testing” is the phase where the new product is built in a limited production fashion with the intent to validate that the design meets the stated specifications through various laboratory and field tests that represent the end use of the product. The manufacturing process is also validated at this time. The outcome of Phase 3 is the release of a design and manufacturing plan that has been validated with a limited production run of the new product design. During this phase of the NPI process the product is tested in an objective manner to ensure that the design has fully met all of the specifications that were defined in Phase 1. As aspects of the design are identified that don’t meet the specifications they must be reviewed at the next gate.

Gate 3 which is referred to as “Begin Volume Manufacturing” is targeted at approving the new product design for full production ramp-up. The results of the product testing and manufacturing processes that occurred in Phase 3 are reviewed. Any issues that were identified in Phase 3 are reviewed and a corrective action plan must be

approved before moving beyond Gate 3. The successful exit of Gate 3 leads to production ramp-up, which means that the design should meet the specifications, the manufacturing and marketing plan should be ready for execution, and the new product delivery date to the market should be finalized.

Phase 4 which is referred to as "Manufacturing Ramp-up" is where the new product is ready for full market introduction and production at volumes that meet market demand. The responsibility for the new product is shifted to the manufacturing organization where the production of the new product is ramped-up while maintaining the product target cost, high levels of quality, adherence to the product performance specifications, and high levels of customer satisfaction. During this phase part of the product design team participates in the production ramp-up to facilitate optimization of the manufacturing process from the product design perspective.

Some companies will have a follow-up phase termed "Cost Reduction" where engineering, manufacturing, purchasing, and the finance departments work together to maximize product value while minimizing cost. Many times product designs are modified to achieve the goal of maximum value at the least cost while maintaining all of the specifications of the new product.

In summary Rosenthal, S. R. (1992) presents a 5 phase and 4 gate new PDP called the NPI process. Depending on the product, some phases and gates of the new PDP may have more or less emphasis. In the end the goal is to manage the development of a new product to meet the stated goals of the new product. The simulation workflow presented in this thesis can be used from Phase 0 to Phase 2, of the NPI process presented by

Rosenthal, S. R. (1992). Traditionally CAE tools have only been used in Phase 2 of the NPI process presented by Rosenthal, S. R. (1992). The framework that is developed as part of this thesis helps bridge the gap between the traditional use of CAE tools, specifically CFD, in the NPI and use of CFD to achieve simulation based design.

Wheelwright, S. C., Clark, K. B. (1992) present a method for determining what a particular company's new PDP should be. A typical PDP that has 5 phases with 4 major milestones is presented. The phases in order of completion are: concept development, product planning and design concept, product and process engineering, pilot production, and production ramp-up. During concept development the product style, conceptual design, and market segment are defined. During the product planning and design concept phase more detailed product designs are developed with limited testing to validate the concept. A detailed financial analysis is developed during the product planning and design phase. During the product and process engineering phase the detailed product design is completed. The detailed processes required to produce the product are also developed in rigorous detail. During this phase prototype products will be built and tested. During the pilot production phase the production processes are validated in the factory environment. Finally in the ramp-up phase production volumes increase to meet market demand.

At the end of the product planning and design concept development phase is the program approval milestone. At this milestone the program is approved to move into the product and process engineering phase in rigor. During the product and process engineering phase the milestone of the first full prototype of the product is built. At the

end of the product and process engineering phase comes the milestone of final engineering release of the product design. Finally the final milestone of market introduction occurs at the end of the ramp-up phase.

Depending on the industry the PDP will be different, as needed for the product being developed, as shown in Figure 18.

Wheelwright, S. C., Clark, K. B. (1992) approach to the PDP is to assist in the development of a process, rather than presenting a proposed PDP. In any case the approach follows the other three approaches presented in this chapter.

EXHIBIT 6–4

Representative Approaches to Project Management

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A. *Overview*	Kodak	General Electric	Motorola	Lockheed Skunkworks
Company's Characterization of the Process	Phases & Gates (Manufacturability Assurance Process — MAP)	Tollgate Process (see Figure 5–4)	Contract-Driven Cross-Functional Teams	Tiger Team
Dominant Characteristics	Strong functional orientation with discipline and focus in the process	Functional orientation, but cross-functional phases and a project team to achieve integration	Team focus with functional support and clear links to senior management	Fully dedicated team with control over resources and process
Key Mechanisms	Phases, gates; customer mission statement; gatekeepers	Tollgates; project manager; senior management review at milestones; cross-functional phases	Dedicated core team; general manager as project leader; the contract; senior management sponsor	Dedicated support resources; co-location; full budget authority; leader as CEO; small, hand-picked team
Major Phases in a Development Project	*6 phases* I. Customer mission/vision II. Technical demonstration III. Technical/operational feasibility IV. Capability demonstration V. Product/process design VI. Acceptance and production	*10 phases* (defined by reviews) I. Customer needs II. Concept III. Feasibility IV. Preliminary design V. Final design VI. Critical producibility VII. Market/field test VIII. Manufacturing feasibility IX. Market readiness X. Market introduction follow-up	*4+ phases* I. Product definition II. Contract development III. Development through manufacturing start-up (team defines subphases) IV. Program wrap-up (learning)	Nonstandard (team specifies major milestones and review procedures for those)
Dominant Type of Project	Manufacturing process; projects where technical advancement is paramount	Evolutions, enhancements, and incremental improvements; technical solutions important but balance across functions crucial; some emphasis on speed	Platform/next-generation; system solution crucial; environment turbulent; speed critical	Breakthrough projects; high risk; experimental efforts
Typical Project Duration	24–40 months	24–48 months	18–30 months	24–60 months
Primary Performance Drivers	a. Resource utilization b. Technical advancement	a. Risk management b. Resource utilization	a. System solution b. Speed	a. Technical performance b. Speed

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B. *Basic Framework Elements*	Kodak	General Electric	Motorola	Lockheed Skunkworks
1. Project Definition	Ideas initiated from many sources; Initial funding can come from any function; "Definition" reflects funding source.	Initial phase is market need definition; Ideas initiated from many sources; Marketing must approve need/opportunity.	Phase I — "Blitz" product definition (7-day limit); Cross-functional; Colocated during definition.	Concept champion emerges (usually a technically trained general manager); Senior management agrees in principle on strategic opportunity; Team details the concept definition.
2. Project Organization and Staffing	Functions control their phase(s) of project; Functions assign people as needed; Work is done by a functional subgroup; Some overlap of R&D/engineering in Phase IV.	Representatives from each function assigned to the team at outset; Team members serve as functional liaisons; Detailed work done in the functions by staff assigned by the functional manager.	Job postings for cross-functional, dedicated/co-located core team; Part-time support groups; Core team responsible for development procedures (within broad corporate guidelines).	Project champion hand picks the team; Team relatively small, people have broad assignments; Most important support people also dedicated and co-located; Other support work subcontracted; Team develops own procedures without constraints.
3. Project Management and Leadership	Shifts from marketing (Phase I) to R&D (Phases II–IV) to engineering (Phases IV–V) to quality assurance and marketing (Phase VI); At phase transitions, a gatekeeper (upstream) releases project, and a stakeholder (downstream) accepts the project.	Program manager maintains schedule, follows up between reviews, facilitates transitions between functions; Functional managers direct the project work done by their people.	Full-time, general manager project head; Core team reports to project head; Project head is concept champion and allocates resources within the project.	Project leader is in charge — CEO of the effort; Does own hiring, training, and evaluation; Manages all aspects; Often creates an entire business unit.

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B. *Basic Framework Elements (continued)*	Kodak	General Electric	Motorola	Lockheed Skunkworks
4. Problem Solving, Testing, and Prototyping	Problem solving and prototyping done largely within the functions; Many specialized test and prototype groups used as subcontractors; Quality assurance does primary testing in Phases V–VI.	Problem solving done largely within single functions; Cross-functional issues raised in reviews and later prototypes; Testing and prototyping done by specialized support groups.	Cross-functional is dominant; Prototypes are project tests, not functional tests; Substantial testing to verify 10X progress.	Cross-functional, but early phases dominated by technical concerns; Emphasis on technical performance on critical dimensions; Engineers work directly with key customer(s) and do own prototypes.
5. Senior Management Review and Control	Senior functional manager does most reviews (their resources and funds); Senior, cross-functional advisory groups used on special issues (e.g., environmental) or to achieve special coordination (e.g., international).	Occurs at key reviews; Strict criteria defined to move to next phase; Emphasis on identifying and managing risks; Management "signs" approval at each tollgate.	Senior management as sponsor and coach; Reviews tied to key project events; Manage to team "contract"; Sponsor is focal point for others on executive staff.	Periodic one-on-one between project leader and corporate top manager; Limited formal reviews, but may hold "communication" exchanges; Senior management sets aggregate resource limits; Team is largely on its own.
6. Real Time/ Midcourse Corrections	Done primarily within single functions; Send projects back to an earlier phase if major problem identified later; Major transition from R&D to engineering (technical feasibility to commercialization).	Senior management involvement in conflict resolution; In concept, vary resources and time line in response to problems; Can halt project at any review if a serious problem.	Low-level problem solving by competent, core team members; Continual, extensive communication; Revise detailed plans periodically; Team changes tasks, their sequences, and groupings.	Do what is required for success; Creative, always trying new ways; Extensive discussions of options and next steps within the team.

Figure 18: Examples of various product development processes. (From Wheelwright, S. C., Clark, K. B. (1992)).

Ulrich, K. T., Eppinger, S. D. (2003) present a generic PDP that includes 6 phases

as shown in Figure 19.

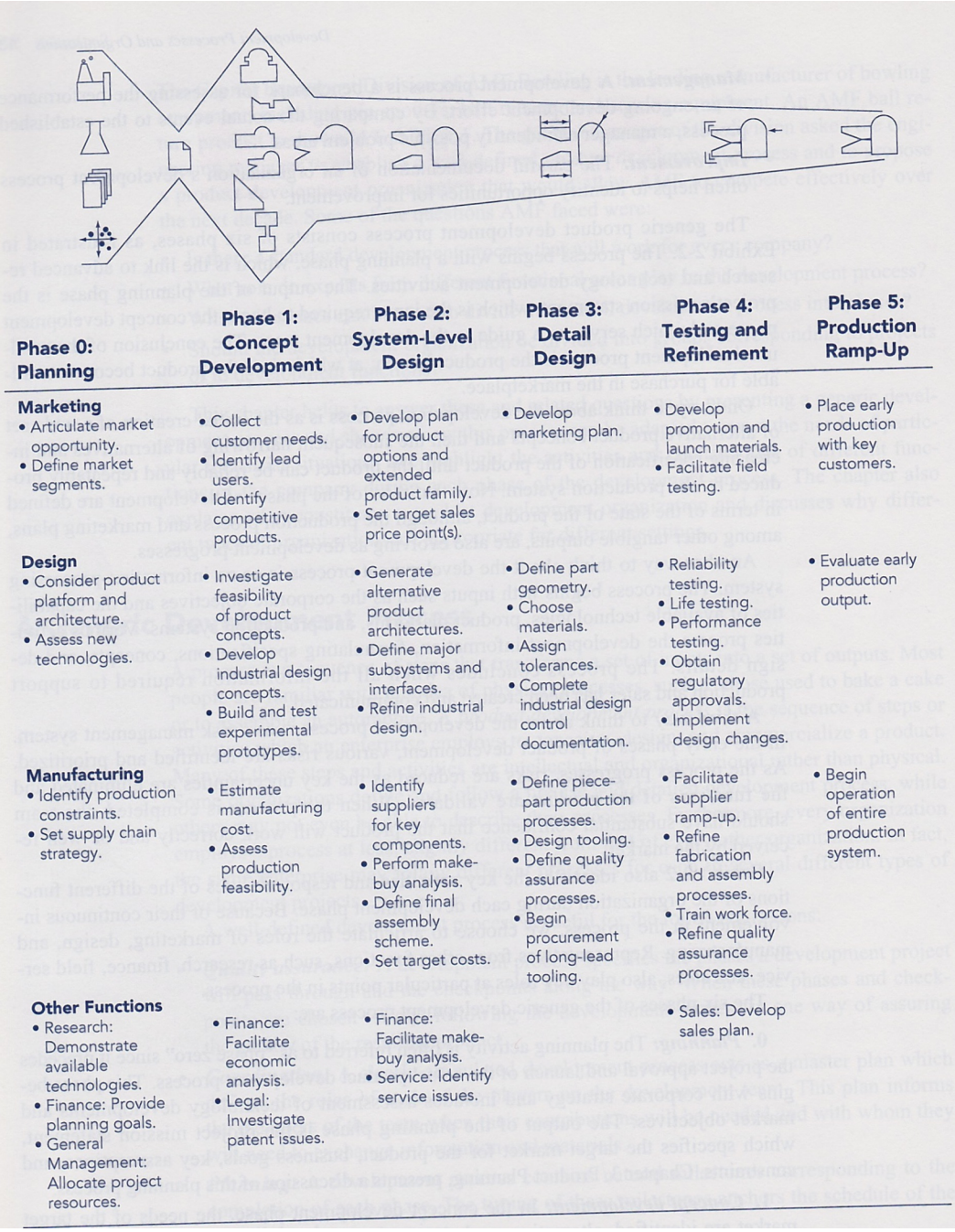

Figure 19: Generic product development process. (From Ulrich, K. T., Eppinger, S. D. (2003)).

In the "Product Planning" phase (phase 0) the new product idea is evaluated to

determine if the new product idea is in alignment with company strategy, what technology is required to develop and produce the new product idea, and the market is studied to understand what the market potential is for the new product idea. One of the outputs of this phase is a project plan that identifies the target market for the new product, company goals for the new product, assumptions made in the project plan, and perceived constraints to the new product plan.

Phase 1 is the "Concept Development" phase where the needs of the target market identified in phase 0 are identified. Many alternate product concepts are developed and evaluated with only a few of the design concepts continuing through the process to further development and testing.

Phase 2 is the "System-level Design" phase where the product architecture is defined and the overall system is divided into sub-systems and components. At the end of this phase a geometric layout and specification of the various sub-systems is completed. A preliminary manufacturing plan including assembly processes is also completed.

Phase 3 is the "Detailed Design" phase where all of the details that embody the product are completed. In this phase geometric, material, and tolerance descriptions of each of the components that makes the overall product is completed. In this phase a bill of material is developed that contains the component identification, quantity, and other information of the components that make-up the product. Generally, component procurement details are worked out in this phase including fabricated internal to the company or purchased from a supplier details. The tooling specifications for parts that

require tooling are developed in detail. In this phase the designs are developed with the goal of having a robust design. Also, during this phase, product cost issues are addressed.

Phase 4 is the "Testing and Refinement" phase of the PDP. Generally this phase involves two physical builds of the product, where these builds verify that the design meets the customer needs, that the product functions correctly as designed, and that the product functions correctly in the end-use conditions. The first build is a design verification build where the design is production intent and a significant number of the components are manufactured from the production intent material but with prototype fabrication processes. This build is used to verify the design. The second build is a production verification build where the design, material, fabrication processes are production intent. This build verifies the product reliability and performance. The assembly process for both physical builds may not be the production assembly process.

Phase 5 is the "Production Ramp-up" phase of the PDP. During the production ramp-up phase the product is produced with all production intent details that embody the product. During this phase the production processes are refined with production units provided to a limited customer group with these units monitored closely to identify any final potential problems. The end of this phase leads to full production where the products are produced in quantities to meet market demand.

In general a summary of a generic new PDP could be derived that has the following phases and gates:

1. Concept Identification

- New Product Specifications

2. Concept Design and Refinement
   - Concept Selection
3. Detailed Design
   - Design Release
4. Product Build and Testing
   - Design Release
5. Limited Production
   - Full Production

Various industries may have more or less phases and gates, but in general there must be a product concept, development of the concept in detail, testing of the product, and production of the new product. This process is the method that a company uses to manage the development of a new product. Of particular interest to this thesis are the concept identification, concept design and refinement, and detailed design phases. If we think of the passenger aircraft it can be described as a large system that is composed of various sub-systems that are composed of components. As an engineer works on the details of the component design CAD, CAE, CAM, design for six sigma, robust design, design for manufacturing, and various other tools are available to the engineer. The focus of this thesis is to develop a framework that allows an engineer to use various CAD and CAE tools, specifically CFD, to make decisions about various component designs. There is often a haphazard relationship between engineering decision making and the data generated with CAE models (simulation models). Often a component design concept is

selected and the design is modified based on results from various simulation models. Often the simulation model is run to understand why a particular component design failed, or the performance is not acceptable. As a component passes through the detailed design and product build and testing phases it is modified and in the end is tailored to whatever flaw is persistent in the component design. The component design will function and meet all goals in the end, but it will not be the most optimum design solution.

Through the use of CAE (simulation) models , specifically CFD, and multi-objective optimization algorithms, various component designs that meet the engineering specifications that are detailed in the concept identification phase of the generic PDP above can be generated. The intended outcome is an optimum design that is tailored to the engineering specifications because the inherent component design flaws are identified and eliminated through the use of appropriate CAE (simulation) models early in the PDP. The workflow developed in this thesis generates Pareto-optimal design solutions that meet the specifications identified in Phase 1 of the generic PDP. This assures that the engineer will be working with optimum design solutions. The second level search algorithm assists the engineer in choosing the design solution or design solutions that are most optimum relative to the specifications.

CHAPTER 3 : THE DETAILED DESIGN PROCESS

In this chapter the methods of detailed product design are reviewed. In general the detailed design of a product falls into the "Detailed Design" phase of the PDP which was reviewed in the previous chapter. First, the mechanical design approach is reviewed with examples followed by the axiomatic design approach.

In product design, the design engineer seeks to determine the design details of a product or system that embodies the design of a product or system in a manner that meets the functional requirements of the product or system. Ullman, D. G. (1997) describes design problems as ill-defined in that the problem statement does not give all of the information required to find a single solution to the problem. The potential solutions to a typical design problem are many with some solutions more optimal than others based on the information given. Ullman, D. G. (1997) uses the following two examples of a lap joint problem to illustrate this point. Consider Problem A which is:

> What size SAE grade 5 bolt should be used to fasten together two pieces of 4 mm thick by 60 mm wide steel plates manufactured from 1045 sheet steel. The two pieces are overlapped at the end and have an axially applied load of 100N.

This problem describes an analysis problem rather than a design problem because the design of the lap joint has been selected as a bolted lap joint. The solution to Problem

A is one where the design engineer needs to understand shear stresses in bolted joints with the desired outcome of the diameter of the grade 5 bolt required to fasten the plates together while not failing under the applied load. Consider Problem B which is:

> Design a joint that fastens two pieces of 4 mm thick by 60 mm wide steel plates manufactured from 1045 sheet steel. The two pieces are overlapped at the end and has an axially applied load of 100N.

The design problem is illustrated in Figure 20.

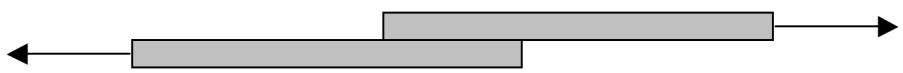

Figure 20: Lap joint problem. (Adapted from Ullman, D. G. (1997)).

Problem B describes a design problem and is a much different problem than Problem A. In Problem A there is 1 solution, whereas there are many potential solutions to Problem B. Problem B is ill defined because the problem description does not appropriately define the constrains on the design solution. Some potential solutions to design Problem B are to bolt the pieces together, use an adhesive to glue the two pieces together, or weld the two pieces together. Before an appropriate design solution can be further developed, it is required to understand more of the constraints on the solution. Does the assembly need to withstand elevated temperature, will it be exposed to a corrosive environment, does the assembly need to be disassembled, will it be painted,

etc? Clearly, more information needs to be known about design Problem B. Generally, the goal in product design is to determine the details of a design solution that meet customer expectations, exhibits high quality, requires the least amount of time, and requires the least commitment of financial resources. Ullman, D. G. (1997) offers that most design problems have no clear optimum solution and have multiple acceptable solutions.

Successful design requires multiple inputs, that are often interrelated, to arrive at a design solution. For example, in the design of an internal combustion engine cooling system, customer requirements are translated to functional requirements that the design must meet. These functional requirements are the input to the design activity. There are also many engineering and business inputs to the design activity which include material properties, fans, pumps, cost, thermodynamics, heat transfer, manufacturing requirements, etc. At the end of the design activity, there can be multiple design solutions that are composed of various combinations of the inputs. Figure 21 shows schematically the inputs and output of a design solution.

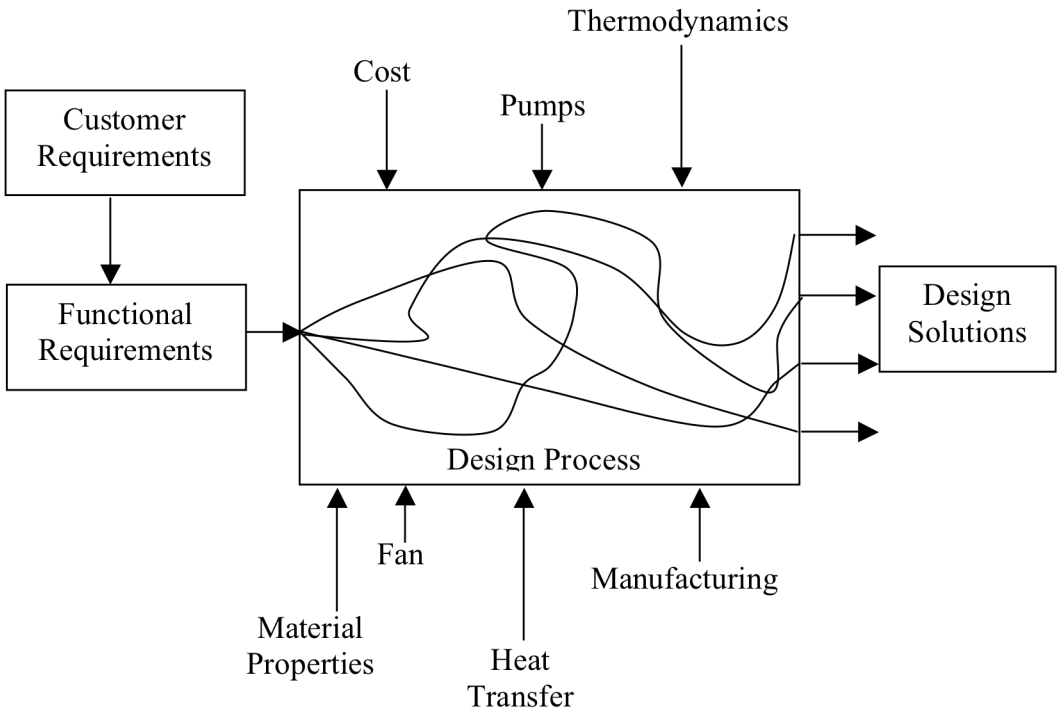

Figure 21: Many solutions to a design problem. (Adapted from Ullman, D. G. (1997)).

Most design problems have the characteristic that multiple solutions exist to the design problem. This characteristic points to a need to evaluate the various design solutions to find the most optimum design solution to the problem. Optimization methods coupled with CAE models can be used to determine the most optimum solution based on the given inputs to the design. Another characteristic of design is the value of information. Generally, early in the PDP little is known about the design problem, but there exists the most design flexibility at this time in the PDP to change the product

design. Later in the PDP more is known about the design problem but the flexibility for changing the design is reduced.

The process of developing a detailed design is characterized by the iterative nature of learning, meaning that the design engineer designs a solution to the design problem, evaluates the solution, updates the design solution, and repeats. During each of these iterations, the design engineer learns more about the design and this new information is incorporated into the next iteration of the detailed design. One of the challenges the design engineer faces is to learn the most about the design problem as early in the PDP as possible, which is when there is the most design flexibility. Again optimization coupled with CAE models can be used to learn more about the design problem earlier in the PDP.

Figure 22 illustrates the concept discussed above. In the past, the problem has been that when the most information is known about the design problem, there is very little design flexibility (late in the PDP) and when there is design flexibility, there is a little known about the design problem (early in the PDP). Abdelsalam, H. M. E., Bao, H. P. (2006), Fiksel, J. (1991), Pichler, R., Smith, P. (2003), Smith, P. G. (1999), Smith, P. G., Reinertsen, D. G. (1998), Smith, P. G., Reinertsen, D. G. (1997) have discussed at length the need for a product to be introduced quickly if the product is to be competitive in the marketplace. Time to market is a significant driver behind the concept of simulation-based design.

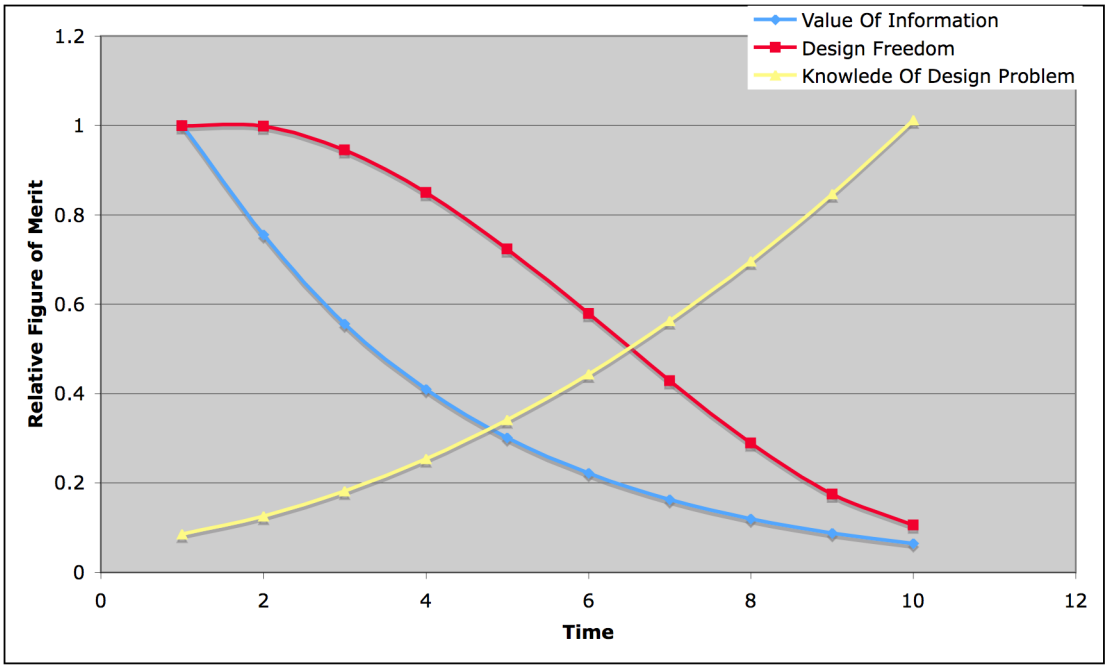

Figure 22: Relative value of information, design freedom, and knowledge of the design problem as a function of time.

The previous discussion highlights the traditional mechanical design problem solving approach. Axiomatic design differs from the traditional approach in that the traditional approach relies on a trial and error approach to design where as axiomatic design performs design on a principle-based basis without the iterative trial and error approach. Suh, N. P. (2001) correlates the empirical trial and error method used in design today to the many design mistakes made today. Further, Suh, N. P. (2001) offers that universities worldwide have not offered engineering students a systematic, codified, or generalized knowledge in design, rather design has been treated as a subject that is not scientific. This has lead to design depending on instinctive reasoning rather than rigorous

scientific study. Axiomatic design treats design as a subject of the arts and sciences rather than just a subject of the arts. Axiomatic design has brought the subject of design much closer to the scientific understanding that other engineering subjects such as heat transfer, fluid mechanics, dynamics, etc have.

Suh, N. P. (2001) defines design as "the interplay between what we want to achieve and how we want to achieve it" with the following activities:

1. Know or understand the customers' needs.
2. Define the problem that must be solved to satisfy the needs.
3. Conceptualize the solution through synthesis.
4. Perform analysis to optimize the proposed solution.
5. Check the resulting design solution to see if it meets the original customer needs.

Once the customers' needs are understood they must be translated into a set of functional requirements that describe what needs to be achieved. The methods used to achieve these functional requirements are described as design parameters. This process of definition and mapping, which is the cornerstone of axiomatic design, is shown in Figure 23. The customer domain defines the needs that the customer desires the product to fulfill (CA). In the functional domain the customer needs are stated as functional requirements (FR) and constraints. In the physical domain design parameters (DP) are chosen that satisfy the functional requirements. To produce the product embodied by the design parameters, process variables (PV) are developed in the process domain.

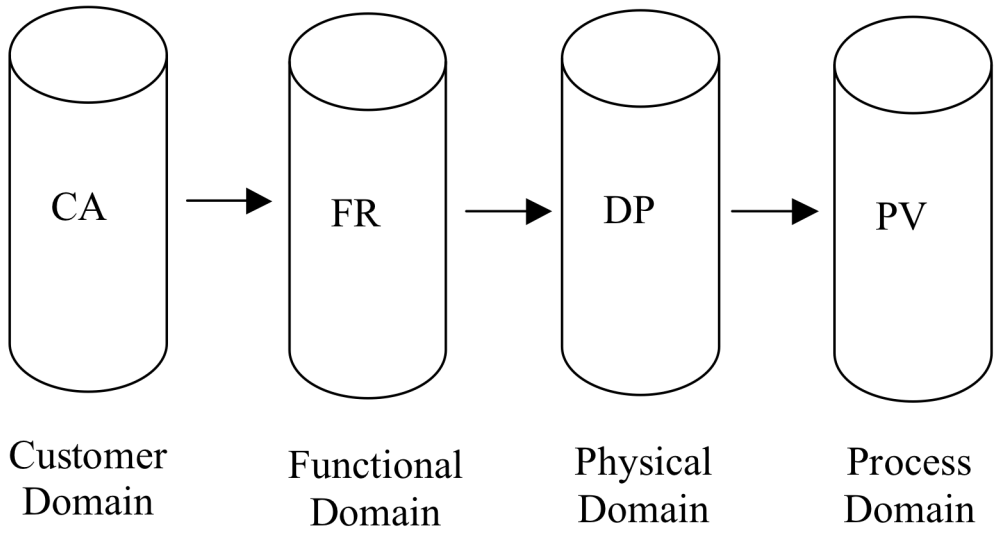

Figure 23: The domains of the design space. (Adapted from Suh, N. P. (2001)).

To understand axiomatic design, the following definitions are provided:

- Axiom: An axiom is a universally accepted, self-evident truth that has no known exceptions or opposites. Axioms are not derived from other laws or principles of nature and don't have detailed algorithmic proofs.
- Theorem: A proposition that is not self-evident but is derived from accepted postulates or axioms and is established as a law or principle.
- Functional Requirement: Functional requirements (FR) are a minimum set of independent requirements that completely defines the function of the product. Each functional requirement is

independent of each other. Functional requirements answer the question of what needs to be achieved and can be thought of as a description of the design goals.

- Constraint: Constraints (C's) are limits on acceptable solutions to the design problem. Input constraints are specified as part of the design requirements. System constraints are implicit constraints in the sense that they are imposed by the particular embodiment of the design solution.
- Design Parameter: Design parameters (DP's) are the physical details that characterize the design that satisfies the specified functional requirements. Design parameters answer the question of how the needs (described in the FR's) are achieved.
- Process Variable: Process variables (PV's) are the variables that describe the process that generates the specified design parameters.

When generating design solutions with the axiomatic approach the customer requirements (CA's) are translated or mapped into functional requirements (FR's). Once the functional requirements are developed the functional requirements need to be mapped into design parameters (DP's) which are the details that embody a design solution to the design problem described by the functional requirements. During the mapping of the FR's from the functional domain (answering the question of what needs to be achieved) to the DP's of the physical domain (answering the question of how the FR's are achieved) good design solutions are governed by two axioms.

- Axiom 1: The Independence Axiom: Maintain the independence of the functional requirements.
- Axiom 2: The Information Axiom: Minimize the information content of the design.

The independence axiom states that when there is more than one FR that during the mapping from the FR's to the DP's (the design process) that a change in one DP only impacts the FR that the particular DP was conceptualized to address. The independence axiom requires that each FR remain independent of other FR's. Axiom 1 may be restated as follows: Suh N. P. (1990)

- Axiom 1
    - Alternate Statement 1: An optimal design always maintains the independence of the FR's.
    - Alternate Statement 2: In an acceptable design, the DP's and the FR's are related in such a way that a specific DP can be adjusted to satisfy its corresponding FR without affecting other FR's.

It is possible to mathematically represent axiom 1. **{FR}** is defined as a functional requirement vector and **{DP}** is defined as the design parameter vector. During the design process the correct set of DP's must be chosen to satisfy the given FR's in such a manner that the design equation, as shown in Equation 5, is satisfied.

$$\{\mathbf{FR}\} = [\mathbf{A}]\{\mathbf{DP}\}$$

Equation 5: Design equation.

The left side of the design equation represents what we want to achieve (design goals) and the right side of the equation shows how we plan to achieve design goals. The matrix **[A]** is defined as the design matrix and is of the form shown in Equation 6

$$[\mathbf{A}] = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mn} \end{bmatrix}$$

Equation 6: Design matrix.

where each element A_{ij} of the design matrix relates a component of the {**FR**} vector to a component of the {**DP**} vector.

Each element of the design matrix may be expressed as shown in Equation 7.

$$A_{ij} = \partial FR_i / \partial DP_j$$

Equation 7: Definition of elements in design matrix.

A_{ij} is a constant for a linear design and A_{ij} is a function of the DP's for a non-linear design. Often the elements of the design matrix are filled in with an "x" indicating a relationship between a DP and FR or a "0" indicating there is not a relationship between the DP and FR.

There are three cases of the design equation that are relevant to the independence axiom.

Case 1: Diagonal design matrix leads to an uncoupled design as shown by Equation 8.

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

Equation 8: Diagonal design matrix.

In this case, all non-diagonal elements of the design matrix are 0, which assures that the design meets the independence axiom because each FR is only satisfied by one DP as shown in Equation 9.

$$FR_1 = A_{11} * DP_1$$
$$FR_2 = A_{22} * DP_2$$
$$FR_3 = A_{33} * DP_3$$

Equation 9: Diagonal design matrix, which leads to an uncoupled design.

Case 2: Triangular design matrix leads to a decoupled design as shown by Equation 10.

$$\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} A_{11} & 0 & 0 \\ A_{21} & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}$$

Equation 10: Lower diagonal design matrix.

In this case, all of the upper triangular elements of the design matrix (or lower triangular elements in an upper triangular matrix) are 0, which assures independence between the FR's if the DP's are adjusted in a particular order. In the case of a lower triangular matrix we must first modify DP_1 to fix the value of FR_1. Now that DP_1 is fixed, we can change DP_2 which now with both DP_1 and DP_2 set FR_2 is now fixed. This process

continues on. This may be thought of as a one-way coupling in that FR_2 depends on DP_1 but DP_1 is defined to meet FR_1 as shown in Equation 11.

$$
\begin{aligned}
FR_1 &= A_{11} * DP_1 \\
FR_2 &= A_{21} * DP_1 + A_{22} * DP_2 \\
FR_3 &= A_{31} * DP_1 + A_{32} * DP_2 + A_{33} * DP_3
\end{aligned}
$$

Equation 11: Lower diagonal design matrix, which leads to a decoupled design.

Case 3: Design matrix with most elements being non-zero leads to a coupled design as shown by Equation 12.

$$
\begin{Bmatrix} FR_1 \\ FR_2 \\ FR_3 \end{Bmatrix} = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \\ DP_3 \end{Bmatrix}
$$

Equation 12: Design matrix with all non-zero elements.

In the three dimensional case, all of the elements of the design matrix are non-zero, which leads to a coupled design. A coupled design exists when a change in FR_i alone cannot occur by changing DP_i because a change in DP_i will also impact FR_{i+1} and FR_{i+2} as shown in Equation 13.

$$FR_1 = A_{11} * DP_1 + A_{12} * DP_2 + A_{13} * DP_3$$
$$FR_2 = A_{21} * DP_1 + A_{22} * DP_2 + A_{23} * DP_3$$
$$FR_3 = A_{31} * DP_1 + A_{32} * DP_2 + A_{33} * DP_3$$

Equation 13: Design matrix with all non-zero elements, which leads to a coupled design.

Of the various design matrices presented, only Case 1 and Case 2 meet the independence axiom. Case 3 is coupled and does not meet the independence axiom due to the coupled nature of the equations. Case 1 meets the independence axiom regardless of the order of mapping the FR's to the DP's. Case 2 meets the independence axiom when the various DP's are fixed in an order such that a change in the DP only impacts the associated FR. Case 3 cannot meet the independence axiom. The design matrix is a second order tensor like stress, strain, or moment of inertia is. These second order tensors can be changed through coordinate transformation to convert any matrix into a diagonal matrix. The diagonal elements of the diagonal matrix are invariant, such as the principal stresses in the case of a stress tensor. The coordinate transformation technique cannot be applied to design equations to find the invariant (the diagonal) matrix, because the design matrix **[A]** involves physical things that are not amenable to coordinate transformations. The best way to take a coupled design to a decoupled or uncoupled design is to redefine the FR's and the DP's to fulfill the FR's.

It is possible that many designs can be conceptualized that satisfy the functional requirements for a given design problem and meet the independence axiom. It is likely that one of the designs is more optimum than the others and as such a method is needed to select the most optimum design solution.

Axiom 2, the information axiom provides a method to evaluate various design solutions and determine the best design solution from the solutions that meet the independence axiom. Simply put, of the design solutions that meet the independence axiom, the design with the minimum amount of information content is the most optimum design. Axiom 2 may be restated as follows: Suh N. P. (1990)

- Axiom 2
    - Alternate Statement: The best design is a functionally uncoupled design that has the minimum information content.

To get a working understanding of axiomatic design it is instructive to review an example. In Suh N. P. (2001) there are many examples that are used to highlight various aspects of axiomatic design. Following is the example of applying axiomatic design to the Newcomen steam engine. The Newcomen steam engine was invented in 1705 by Thomas Newcomen and was used to pump water out of coal mines. The Newcomen engine works by injecting steam into a cylinder to push a piston outward to lower the piston in the water pump located in the mine. Once the piston in the water pump reaches the lowest point, it is raised by condensing the steam in the cylinder, which creates a vacuum inside the cylinder, which pulls the piston inward. The work done by the piston/cylinder that is attached to the boiler is used to pump water out of the mine. The

steam in the cylinder is condensed by spraying cool water into the cylinder, which lowers the temperature of the steam, which causes condensation. During the next cycle steam is injected into cylinder, which raises the temperature of the cylinder and drives the condensed water out of the cylinder before the steam can fully expand and raise the piston again, repeating the cycle. Figure 24 illustrates the Newcomen engine not

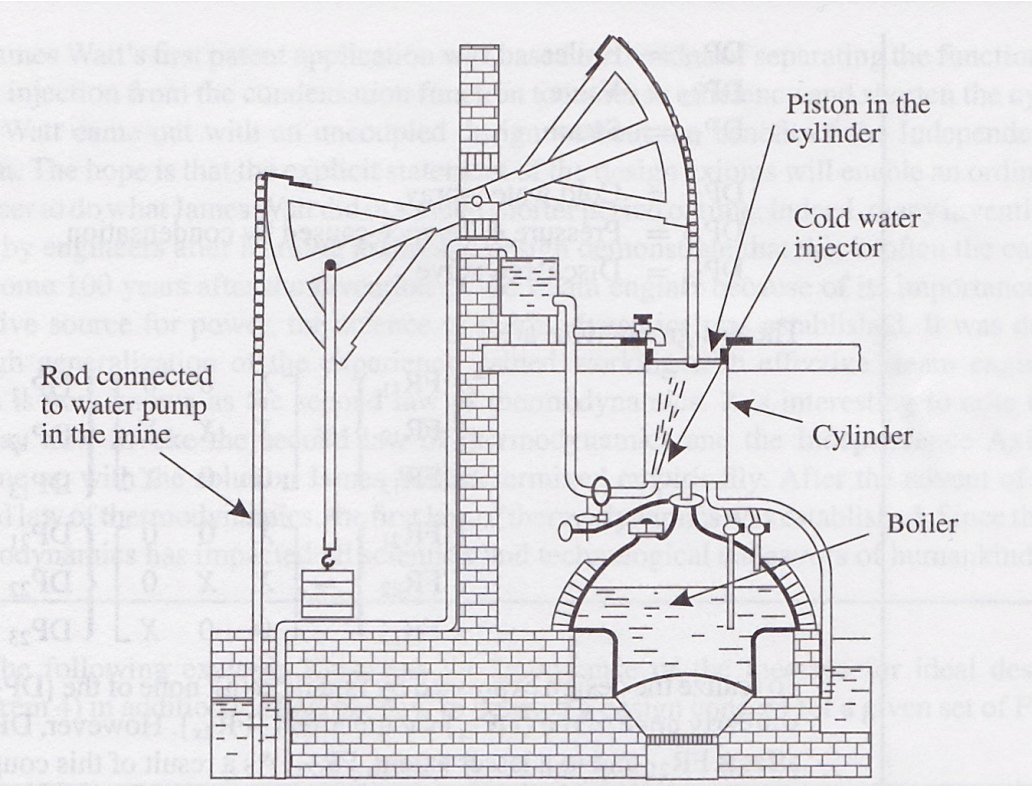

Figure 24: Newcomen engine schematic without the pump located in the mine. (From Suh N. P. (2001)).

showing the pump located in the mine.

Simply put the customer requirement is to pump water out of the mine. The functional requirements at the highest level are as:

FR_1 = Extend the piston.

FR_2 = Contract the piston by creating a vacuum in the cylinder.

The design parameters are:

DP_1 = Pressure of the steam.

DP_2 = Vacuum in the cylinder/piston by condensation of the steam.

The ideal design equation is written as shown in Equation 14.

$$\begin{Bmatrix} FR_1 \\ FR_2 \end{Bmatrix} = \begin{bmatrix} X & 0 \\ 0 & X \end{bmatrix} \begin{Bmatrix} DP_1 \\ DP_2 \end{Bmatrix}$$

Equation 14: Newcomen engine ideal design equation.

Subsequent design decisions made at lower levels of decomposition must be consistent with the design decision represented by Equation 14 in that the lower level design decisions must maintain the off-diagonal elements as zero. FR_1 may be decomposed as:

FR_{11} = Generate steam.

FR_{12} = Inject steam.

FR_{13} = Expand the steam and move the piston outward.

FR_2 may be decomposed as:

FR_{21} = Condense steam.

FR_{22} = Move the piston inward.

FR_{23} = Discharge the condensate.

The design parameters are as follows:

DP_{11} = Boiler.

DP_{12} = Valve.

DP_{13} = Steam.

DP_{21} = Cold water spray.

DP_{22} = Pressure difference caused by condensation.

DP_{23} = Discharge valve.

The design equations are written as shown in Equation 15.

$$\begin{Bmatrix} FR_{11} \\ FR_{12} \\ FR_{13} \end{Bmatrix} = \begin{bmatrix} X & 0 & 0 \\ X & X & X \\ 0 & 0 & X \end{bmatrix} \begin{Bmatrix} DP_{11} \\ DP_{12} \\ DP_{13} \end{Bmatrix}$$

$$\begin{Bmatrix} FR_{21} \\ FR_{22} \\ FR_{23} \end{Bmatrix} = \begin{bmatrix} X & 0 & 0 \\ X & X & X \\ 0 & 0 & X \end{bmatrix} \begin{Bmatrix} DP_{21} \\ DP_{22} \\ DP_{23} \end{Bmatrix}$$

Equation 15: Lower level design equations.

To realize the design described by Equation 14 none of the $\mathbf{DP_{2X}}$ should affect the $\mathbf{FR_{1X}}$ and similarly none of the $\mathbf{DP_{1X}}$ should affect $\mathbf{FR_{2X}}$. DP_{21} affects FR_{13} and DP_{13} affects FR_{21} and to a lesser extent FR_{22}. As a result of this coupling, DP_1 affects both FR_1 and FR_2 because the steam has to heat the cylinder and the piston before the injected

steam can expand in the cylinder. Similarly, DP_2 affects both FR_1 and FR_2 because when the cold water is sprayed around the cylinder, the cylinder and the piston have to be cooled before the steam inside the cylinder can be condensed. Therefore, the design matrix of Equation 14 is not diagonal or triangular and cannot be realized with the current design of the Newcomen engine. The Newcomen engine is a coupled design and as such violates the independence axiom.

This coupled design can be uncoupled by creating a separate condenser elsewhere, which will condense the steam ejected from the cylinder. This is the invention James Watt made in 1769. The Watt engine was successful because it had a higher efficiency. Further, the Watt engine is an uncoupled design which meets Axiom 1 of axiomatic design. In Watt's engine, the FR's can be satisfied independently.

Engineering design problems have the characteristic that they are ill posed in that there are often many solutions to the design problem. The lap joint example shows that when all of the constraints are not defined for the design solution the problem is ill defined. The lap joint example where the engineer simply needs to determine the size of a grade 5 bolt to fasten the two pieces of steel together can be thought of as an analysis problem. In detailed design it is desirable to think outside the box with few constraints with the goal of generating a wide range of ideas, whereas in design analysis the constraints and acceptance criteria must be specified so that a particular design solution can be evaluated. The method presented in this thesis seeks to bridge the gap between design and analysis by developing workflows that allow the engineer to specify the design parameters (design variables), design constraints and acceptance criteria of a

system or component (cooling system, exhaust gas after-treatment system, jet pump, etc) and use CFD models coupled with multi-objective optimization algorithms to determine a set of Pareto-optimal design solutions to the design problem. The detailed definition of Pareto-optimal will be reviewed in the chapter on multi-objective optimization. In short, Pareto-optimal design solutions are those design solutions that meet all of the acceptance criteria, but have different design variables to do so.

This is helpful in the traditional mechanical design process because this workflow now allows the engineer to evaluate multiple design solutions to a design problem. In the lap joint design problem that is ill posed the addition of a few constraints would allow the engineer to determine a set of design solutions that are Pareto-optimal and meet the acceptance criteria and constraints. The utility of this is that as the design progresses through the PDP additional constraints or more details about existing constrains will be known. With a set of design solutions (Pareto-optimal set) the engineer can then start to determine what design solutions best meet the new or more detailed constraints. This method also allows the engineer to choose the "optimal" design based on higher-level information.

In axiomatic design, the method presented in this thesis can be used to determine the details of the design parameters during the mapping from functional requirements (what we want to achieve) to the design parameters (how we want to achieve it). In most product development processes all of the details of schedule, cost, weight, max stress, maximum deflection, heat rejection among other characteristics of systems are not known. If the engineer is able to provide multiple sets of design parameters to the

constrains and functional requirements that are known at a given time in the PDP the engineer is better suited to address the ever present changes in constraints and functional requirements that occur in the PDP. Further, with the addition of the higher-level information the design can progress through the PDP in a shorter amount of time.

CHAPTER 4 : MULTI-OBJECTIVE OPTIMIZATION

As the name suggests multi-objective optimization, sometime called vector optimization, problems deal with more than one objective function. In most engineering design problems, multiple objectives are present. Because of the lack of suitable solution methodologies, multi-objective optimization problems have been cast and solved as single-objective optimization problems in the past. The fundamental difference between a single-objective and multi-objective optimization problem is that the single-objective optimization problem is seeking to find one solution to the optimization problem (except in the case of a multi-modal optimization problem with multiple optimal solutions). A multi-objective optimization problem may not have the task to find one optimal solution to each objective function, rather a Pareto-optimal set of solutions is desired. In problems with one or more conflicting objectives, there is no single optimum solution in the absence of higher-level (additional) information. There exists a number of solutions which are all optimal. In the absence of higher-level information, no solution from the set of optimal solutions can be said to be better than any other. Another difference between single-objective optimization and multi-objective optimization is that the objectives in the multi-objective problem form a multi-dimensional objective space in

addition to the multi-dimensional design variable space. In single-objective optimization the objective space is one-dimensional because there is one objective function.

A multi-objective optimization problem has more than one objective function, which are to be minimized or maximized. As in the single-objective optimization problem, the multi-objective optimization problem has a number of constraints, which any feasible solution must satisfy.

The multi-objective optimization model is defined as follows: Find a vector of design variables, shown in Equation 16

$$\mathbf{x} = (x_1, x_2, x_3, \ldots x_n)$$
$$x_n^{(L)} \leq x_n \leq x_n^{(U)};\ n = 1,2,\ldots,N$$

Equation 16: Solution vector of design variables.

that maximize or minimize the objective functions, shown in Equation 17,

$$f(\mathbf{x})_i = f(x_1, x_2, \ldots, x_n)_i; \quad i = 1,2,\ldots,I$$

Equation 17: Multi- objective optimization problem objective functions.

subject to the J equality constraints, shown in Equation 18,

$$h_j(\mathbf{x}) = h_j(x_1, x_2, \ldots, x_n) = 0; \quad j = 1, 2, \ldots, \mathrm{J}$$

Equation 18: Multi-objective optimization problem equality constraints.

and subject to M inequality constraints, shown in Equation 19,

$$g_m(\mathbf{x}) = g_m(x_1, x_2, \ldots, x_n) \leq 0; \quad m = 1, 2, \ldots, M$$

Equation 19: Multi-objective optimization problem inequality constraints.

where J is the total number of equality constraints, and M is the total number of inequality constraints. Each design variable shown in Equation 16 is subject to the upper bound $x^{(U)}$ and lower bound $x^{(L)}$ constraints. These upper and lower bounds represent the maximum and minimum values of the design variables.

From a practical standpoint, a user needs only one solution to a problem, regardless if the problem is multi-objective or single-objective. In the case of a multi-objective problem the user now needs to determine which of the optimum solutions to pick from. This is where the user needs to use the higher-level, information to facilitate making the decision on which solution to choose. The ideal multi-objective optimization procedure can be described as follows:

Step 1: Find multiple trade-off optimal solutions (Pareto-optimal solutions) with a wide range of values for objectives.

Step 2: Choose one of the obtained solutions using higher-level information.

Figure 25 shows these steps schematically where step one involves defining the problem and using the optimizer to generate the multiple tradeoff solutions. Step 2 involves using higher-level information to choose one solution (Deb, K. 2001).

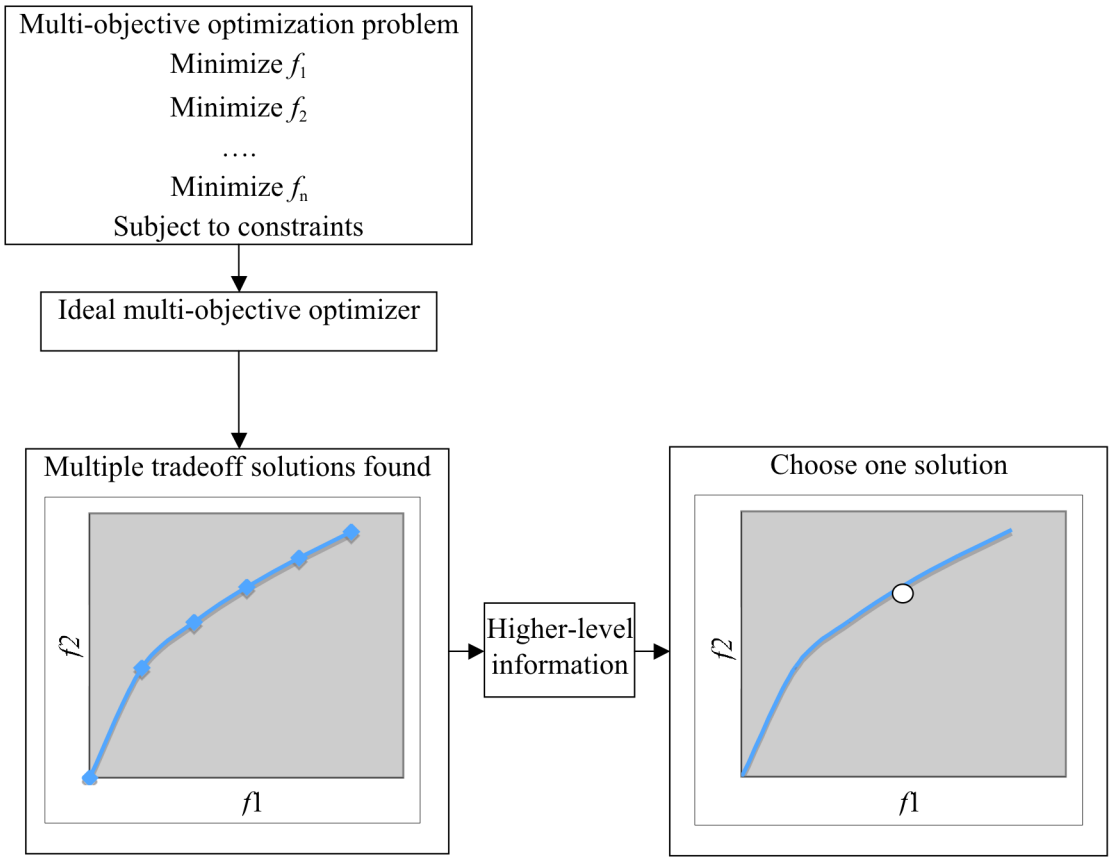

Figure 25: Schematic of ideal multi-objective optimization procedure. (Adapted from Deb, K. (2001)).

Multi-objective optimization problems have the characteristic that they have multi-dimensional objective space, which many design problems also exhibit. In design problems the performance metric or product outputs are analogies to the objectives. This makes multi-objective optimization an excellent method for determining the multiple design solutions to the design problem. For each solution **x** in the design variable space, there exists a point in the objective space, $\mathbf{f}(\mathbf{x}) = \mathbf{f} = (f_1, f_2, \ldots, f_m)$. The mapping between

the two spaces occurs through an n-dimensional design variable vector and an m-

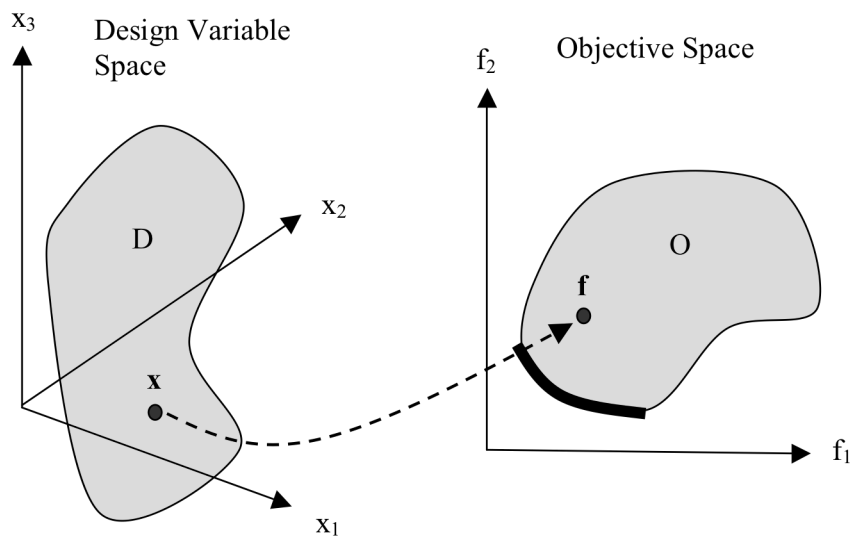

Figure 26: Design variable space and corresponding objective space.

dimensional objective vector as shown in Figure 26.

A multi-objective optimization problem may not have the task to find a single optimal solution to each objective function; rather a Pareto-optimal set of solutions is desired. In problems with one or more conflicting objectives, there is no single optimum solution. There exist a number of solutions, which are all optimal. This leads to the concept of non-dominated and dominated points. A vector of objective functions, $\mathbf{f}(\mathbf{x}^*) \in O$, is non-dominated if another vector $\mathbf{f}(\mathbf{x}) \in O$ does not exist such that $\mathbf{f}(\mathbf{x}) \leq \mathbf{f}(\mathbf{x}^*)$ with at least one $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$. Stated another way, an objective solution f1 is said to dominate a solution f2, if the solution f1 is no worse than f2 in all objectives and the solution f1 is

strictly better than f2 in at least one objective. If the above conditions are not met the solution f1 does not dominate the solution f2. Finally, a design variable vector $\mathbf{x}^* \in D$ is Pareto-optimal if there does not exist another design variable vector $\mathbf{x} \in D$ such that $f_i(\mathbf{x}) \leq f_i(\mathbf{x}^*)$ for all i=1,2,…,I and $f_j(\mathbf{x}) < f_j(\mathbf{x}^*)$ for at least one index j. An objective vector $\mathbf{f}^* \in O$ is Pareto-optimal if there does not exist another objective vector $\mathbf{f} \in O$ such that $f_i \leq f^*_i$ for all i=1, 2, …I and $f_j < f^*_j$ for at least one index j. Alternately the objective vector $\mathbf{f}^*$ is Pareto-optimal if the design vector corresponding to it is Pareto-optimal (Steuer, R. E. (1989), Deb, K. (2001), Mietinen, K. M. (1999)). The bold line in the objective space of Figure 26 shows the Pareto-optimal objective space vector. For a design problem this would be the set of Pareto-optimal solutions to the design problem.

In multi-objective design problems the engineer is interested in the Pareto-optimal objective space vector because the vector represents multiple potential optimum solutions to the design problem. The engineer can then choose an optimal solution from the Pareto-optimal objective vector and map back to the design variable space to determine the specific values of the design variables required to produce the chosen solution to the design problem.

The multi-objective optimization algorithm used in this thesis is based on the Genetic Algorithm (GA). Following is a brief introduction to genetic algorithms as presented in Deb, K. (1999). The concept of a genetic algorithm was first introduced by John Holland of the University of Michigan, Ann Arbor (Holland, J., H. 1975). Genetic algorithms are widely used in engineering design and optimization to optimize both single and multi-objective optimization problems (Gen, M., Cheng, R. (1997), Li, J., P.,

Balazs, M., E., Parks, G., T. (2007), Oksuz O., Akmandor I. S. (2010), Marler, R., T., Arora, J., S. (2004)).

Genetic algorithms use the methods of natural genetics and natural selection as the motivation for their search and optimization procedures. To illustrate the workings of a genetic algorithm, a genetic algorithm will be developed for a simple cylindrical can. The cylindrical can has two design variables, the diameter and the height of the can. A constraint is applied that the can must have a volume greater than or equal to 300 ml. The objective of the optimization problem is to minimize the cost of the material used to make the can. The nonlinear programming optimization problem. Equation 20 shows the objective function which contains the design variables of diameter *d* and height *h* as well as the cost of the material *c* the can is manufactured from. The design variables *d* and *h* are allowed to vary between a physically reasonable minimum and maximum

$$f(d,h) = c\left(\left(\frac{\pi d^2}{2}\right) + \pi dh\right)$$

Equation 20: Objective function of optimization problem.

value.

Equation 21 shows the constraint that the optimum can design solution must have a volume greater than or equal to 300ml.

$$g(d,h) = \left(\frac{\pi d^2 h}{4}\right) \geq 300$$

Equation 21: Inequality constraint.

Before a genetic algorithm can be used to find the optimum design parameter values that satisfy the constraint *g* while minimizing the objective function *f* the design variables need to represented as binary strings. In this case five bit strings will be used to code the design variables as shown in Equation 22.

$$d = 01000$$
$$h = 01010$$

Equation 22: Coded design variables.

With the coding of the design variables chosen both design variables have a minimum value of 0 and a maximum value of 31. With five bit coding there are 2^5 possible design solutions.

Coding of the design variables into binary strings is performed so that the design solution is represented as a pseudo-chromosome. The 10 bit string that represents the can design solution shown above represents a can that has a diameter of 8 cm and a height of 10 cm. Natural chromosomes are composed as many genes, with each gene taking various allelic values. To understand how the 10 genes in the coded representation of the

can shape, first consider the left most bit in the diameter design parameter. A value of 0 at this bit allows the can to have a diameter between 0 and 15 and when the value of this bit is 1 it is possible for the can to have a diameter between 16 and 31.

Once a string representing the design variables is defined it is necessary to evaluate the design solution against the constraints and the objective function. This evaluation is referred to as the string fitness evaluation. In the can design case the objective is to minimize the cost of the can so lower fitness values represent more fit design solutions. Figure 27 shows a flowchart of the basic operating principle of a genetic algorithm.

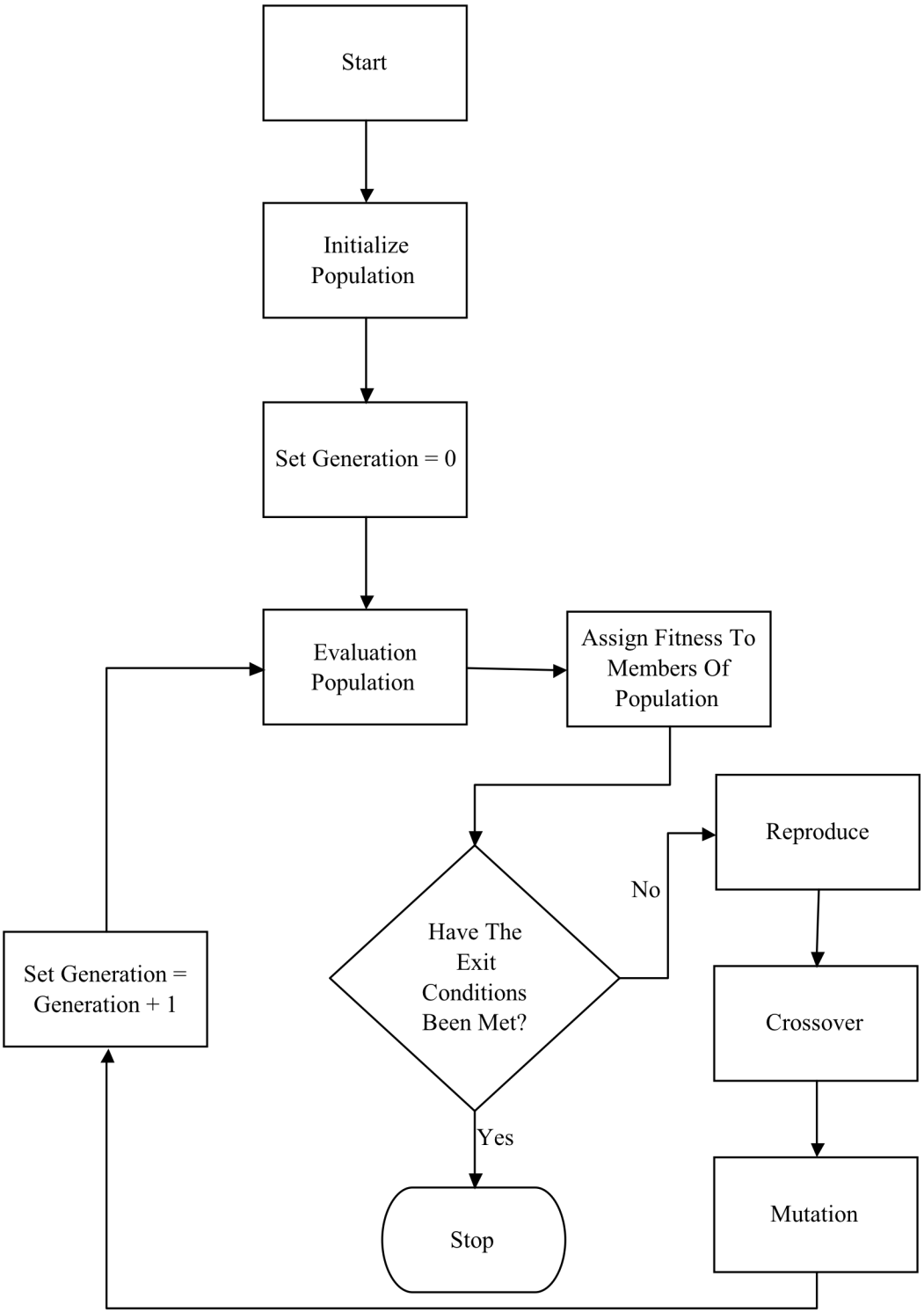

Figure 27: Flowchart of the basic working principle of a genetic algorithm. (Adapted from Deb, K. (2001)).

Once the genetic algorithm is started, an initial population containing multiple members that are composed of coded design variables is created. Each member of the population (design solution) is evaluated according to Equation 20 and Equation 21 to assign fitness to each member of the population. Next the algorithm will check to see if the exit conditions for the search have been met, which is often a maximum number of generations. If the exit conditions have been met the algorithm stops and if the exit conditions have not been met the population of design solutions is modified by executing a reproduction, crossover, and mutation operator on the population in an effort to create a new and hopefully better fit population. Finally the generation counter is incremented and the process continues.

The reproduction operator is used to emphasize highly fit (good) design solutions and eliminate lower fit (bad) design solutions from the population while maintaining the population size as constant. This operation is usually performed with the following tasks:

1. Identify above-average design solutions in a population.
2. Make multiple copies of the above-average design solutions.
3. Eliminate the bad design solutions from the population to make room in the population for the copied above-average design solutions.

There are a number of ways to achieve the above tasks, with common methods being tournament selection, proportionate selection, and ranking selection among others (Goldberg, D., E., Deb, K. 1991). For illustration purposes tournament selection is reviewed here. In tournament selection, tournaments are played between two design solutions and the design solution with the better fitness value (can cost in this case) is

chosen to be in the new population. Two other design solutions are chosen again and the design solution with the better fitness is added to the new population. When tournament selection is implemented systematically each design solution will participate in two tournaments. The best design solution in the current population will win both of its tournaments and as such the best design solution will be placed in the new population twice. In the same fashion, the worst solution will loose both tournaments and will not be added to the new population. With this implementation of tournament selection any design solution will have zero, one, or two copies in the new population. Inherently tournament selection ensures that the best design solutions of the previous population are carried into the new population. At this point in the genetic algorithm process the new population has only the design solutions that won their tournaments, which is commonly referred to as the mating pool. The mating pool now undergoes crossover.

The crossover operator is the primary means for creating new design solutions from the mating pool. There exists a number of different crossover operators in the literature as shown in Spears, W., M., De Jong, K., A. (1991). The common thread in most crossover operators is that two bit strings are chosen at random from the mating pool and some portion of the strings are exchanged between the two bit strings. In single-point crossover a bit location in the bit strings is chosen at random and all of the bits to the right of the selected bit location are exchanged between the two bit strings. Equation 23 shows single-point crossover, at the third bit in the stings, between two design solutions in the mating pool having a fitness of 23 and 37. The two created design solutions have a fitness of 22 and 39. Not all of the mating pool strings will participate in

crossover. A crossover probability p_c is used to determine how many population members will participate in crossover (100%*p_c). The population members that do not participate in crossover are kept in the new population unchanged. Deb, K. (1999)

$$(d = 8,\ h = 10 : f = 23)\ 01000\ 01010 \qquad 01010\ 00110\ (d = 10,\ h = 6 : f = 22)$$

$$(d = 14,\ h = 6 : f = 37)\ 01110\ 00110 \qquad 01100\ 01010\ (d = 12,\ h = 10 : f = 39)$$

Equation 23: Single-point crossover. (Adapted from Deb, K. (1999)).

contains a discussion about crossover and mutation creating population members with better or worse fitness than the parents of the new population member.

The crossover operator is the primary method responsible for searching the design space. The mutation operator is also used for searching the design space, but is used sparingly with the primary intent to maintain diversity in the design solutions in a population. The mutation operator takes a design solution that has been through reproduction and crossover and randomly changes a 1 to a 0 or a 0 to a 1 in the bit string of the design solution. The mutation operator is applied to a small number of population members as controlled by a mutation probability p_m.

After the reproduction, crossover, and mutation operators are complete, the generation counter is incremented and the new population (generation n+1) fitness is evaluated and the process continues until a maximum number of generations has been

reached as determined at the start. The literature contains many excellent papers on genetic algorithm operation with Deb, K. (1999), Deb, K. (2001), Holland, J., H. (1975), Goldberg, D., E. (1989), Michalewicz, Z. (1992), Mitchell, M. (1996), and Gen, M., Cheng, R. (1997) being excellent sources of information.

The workflow developed in this thesis uses the Neighborhood Cultivation Genetic Algorithm (NCGA) (Watanabe, S., Hiroyasu, T., Mike, M. 2002) as the multi-objective optimization algorithm for the Level-1 optimization. The NCGA algorithm is characterized by its unique crossover operation. The crossover operation is performed on design solutions in the population that are close to each other. This differs from the genetic algorithm outlined earlier in that crossover occurs on design solutions chosen at random. By choosing design solutions for crossover that are close to each other, NCGA is exploiting the most fit parent design solutions by producing new design solutions from the most fit parents, rather than randomly choosing the parents for reproduction. NCGA handles the multiple objectives in a sequential fashion. Generation 1 finds the best design solution to objective 1, generation 2 finds the best design solution to objective 2, with generation n finding the best design solution to objective n.

The NCGA algorithm was chosen for this framework based on its effectiveness at finding Pareto-optimal design solutions in the least number of iterations for the test problems shown in Watanabe, S., Hiroyasu, T., Mike, M. (2002).

CHAPTER 5 : DESIGN METHODOLOGY

In the previous chapters, an overview of the work presented in this thesis was provided, a review of the pertinent literature was summarized, the PDP, as well as the detailed design process was reviewed, and an overview of multi-objective optimization was covered. In each of these chapters the relevant elements of the method presented in this thesis were reviewed.

This chapter is intended to summarize the design methodology used to solve the problem of *integrating CFD models earlier in the PDP to facilitate engineering decision making early in the PDP*. To solve this problem, a multi-objective, multi-level optimization method is used whereby CAD models and CFD models are exploited to search the design space to find the Pareto-optimal design solution set (Level-1) and a user in the loop search algorithm searches the Pareto-optimal design solutions to determine which Pareto-optimal design solution is the optimum solution (Level-2).

In this framework, the process shown in Figure 28 is used to generate the Pareto-optimal design solutions to the design problem.

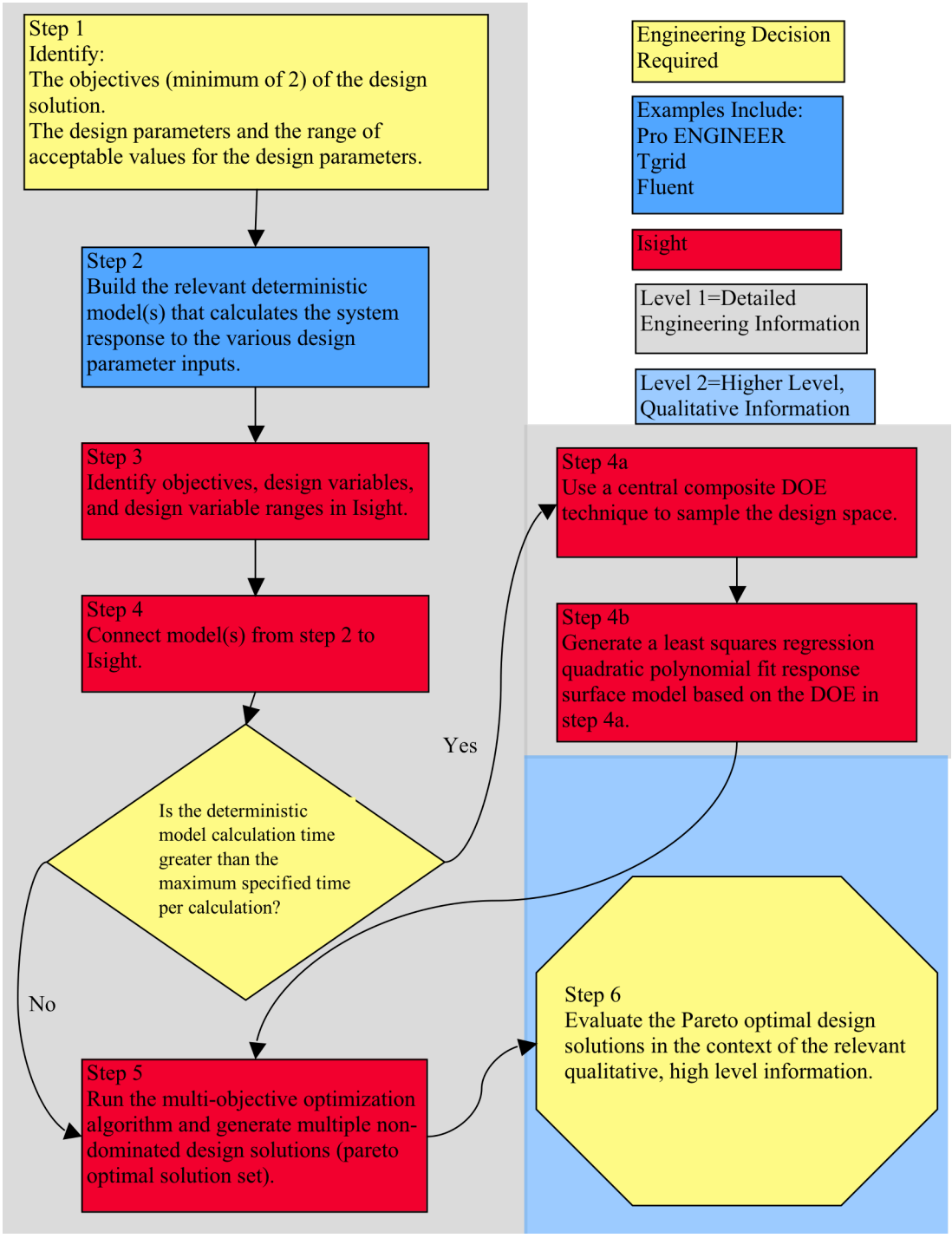

Figure 28: Process to generate Pareto-optimal design solutions to the design problem (Level-1 optimization).

This process assumes that the design problem is defined a priori. In Step 1 the

objectives of the design solution (functional requirements), the design variables, and the range of acceptable values of the design variables are defined. Examples of the objectives of the design solution could be: minimize pressure drop, maximize mass flow, minimize frontal area, minimize power consumption, etc. In Step 2 the appropriate CFD model (deterministic model) is built to calculate the system response to the various design variables. In Step 3 and Step 4 the model from Step 2 and the objectives and design variables from Step 1 are connected in the simulation workflow software Isight. After Step 3 the engineer needs to decide if a response surface model should be generated or if the CFD model can be used directly by the multi-objective optimization algorithm. In the method presented in this thesis, calculation time of the CFD model is used as the decision criteria. If the CFD model runs in less than a specified amount of time, as determined by the user, per run it is likely the time to achieve the Pareto-optimal design solutions will be acceptable. If the calculation time is greater than the user specified maximum runtime, a central composite design of experiments is used to sample the design space to generate a response surface model. In a central composite design the number of calculations is 2^n+2n+1 where n is the number of design variables (Montgomery, D., G. 2005). In the case where the response surface model technique is used, the multi-objective optimization algorithm uses the response surface model to calculate the system response (objective) at the various design variables. In the case where a response surface in not used, the CFD model (deterministic model) is used to evaluate the system directly by the multi-objective optimization algorithm. In Step 5 the multi-objective optimization algorithm evaluates the system response based on the

combination of various design parameter inputs in the search for the Pareto-optimal design solutions. In Step 6 the engineer can then evaluate the Pareto-optimal design solutions in the context of the higher-level, qualitative information to make a decision as to which design solution is optimum.

The process to generate the Pareto-optimal design solutions is characterized by a software framework that uses a multi-objective optimizer, simulation workflow execution engine, CAD software, CFD mesh generation software, CFD solver, and CFD results post processing as shown in Figure 29. The top simulation workflow optimizes directly on the CFD model, and the lower simulation workflow optimizes on a response surface model that is generated from the results of a central composite design of experiment. The framework demonstrated in this thesis is designed to be general purpose, which allows it to be applied to various types of problems as well as various types of software. The framework is demonstrated in this thesis with connection to CFD models, but it is extensible to the use of FEA software, 1-D system simulation, process simulation, and other simulation models.

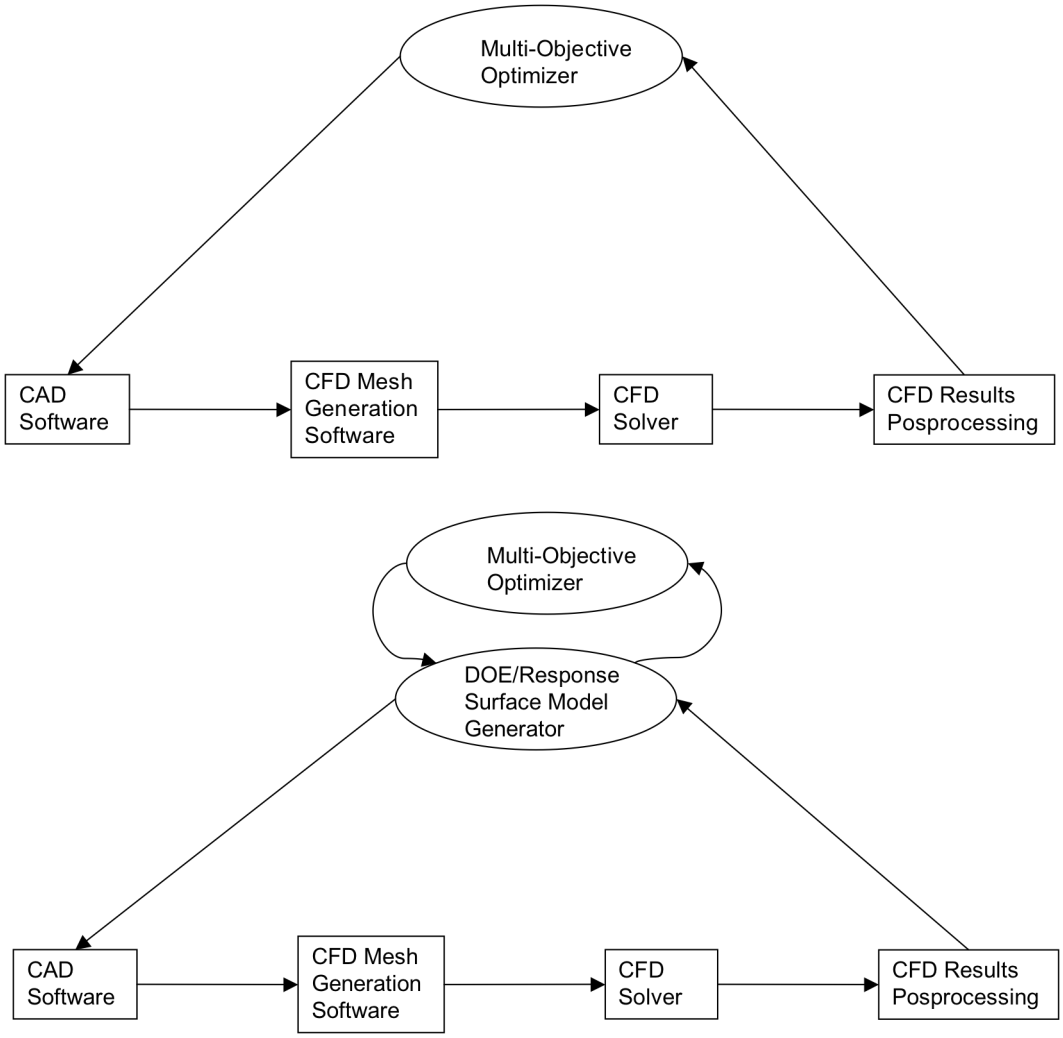

Figure 29: Simulation workflow framework (Level-1 Optimization).

At the completion of the Level-1 optimization there exists a Pareto-optimal set of designs to the design problem. Ideally the Pareto-optimal design solution set will include more than 50 design solutions to the design problem. In the absence of additional information each of the designs in the Pareto-optimal set are equally optimum (CHAPTER 1 and CHAPTER 3 contain more information on Pareto-optimality).

Practically the engineer needs one design solution or in some cases a much smaller subset of the Pareto-optimal set to move through the PDP. This leads to the need for the Level-2 optimization framework that is developed in this thesis.

During the Level-2 optimization, the engineer evaluates the Pareto-optimal design solutions against higher-level information. This higher-level information is often related to the PDP. Examples of this information are cost, schedule, manufacturability, quality, reliability, and supply-chain among others. In this method higher-level information is any information that is available at the time the Level-2 optimization is completed. The Level-2 optimization algorithm that was developed to assist the engineer in evaluating the design solutions; searches the Pareto-optimal design solution set presenting the engineer with a predetermined number of design solutions *n* for evaluation. This sub-set of Pareto-optimal design solutions is referred to as the evaluation set. The engineer chooses which design solution is the most optimum of the evaluation set. The optimization algorithm then retains the chosen design solution in the Pareto-optimal set and eliminates the other design solutions from the Pareto-optimal set. This process continues until all of the design solutions in the Pareto-optimal set have been evaluated or the engineer terminates the process. Figure 30 shows the Level-2 optimization algorithm flow chart.

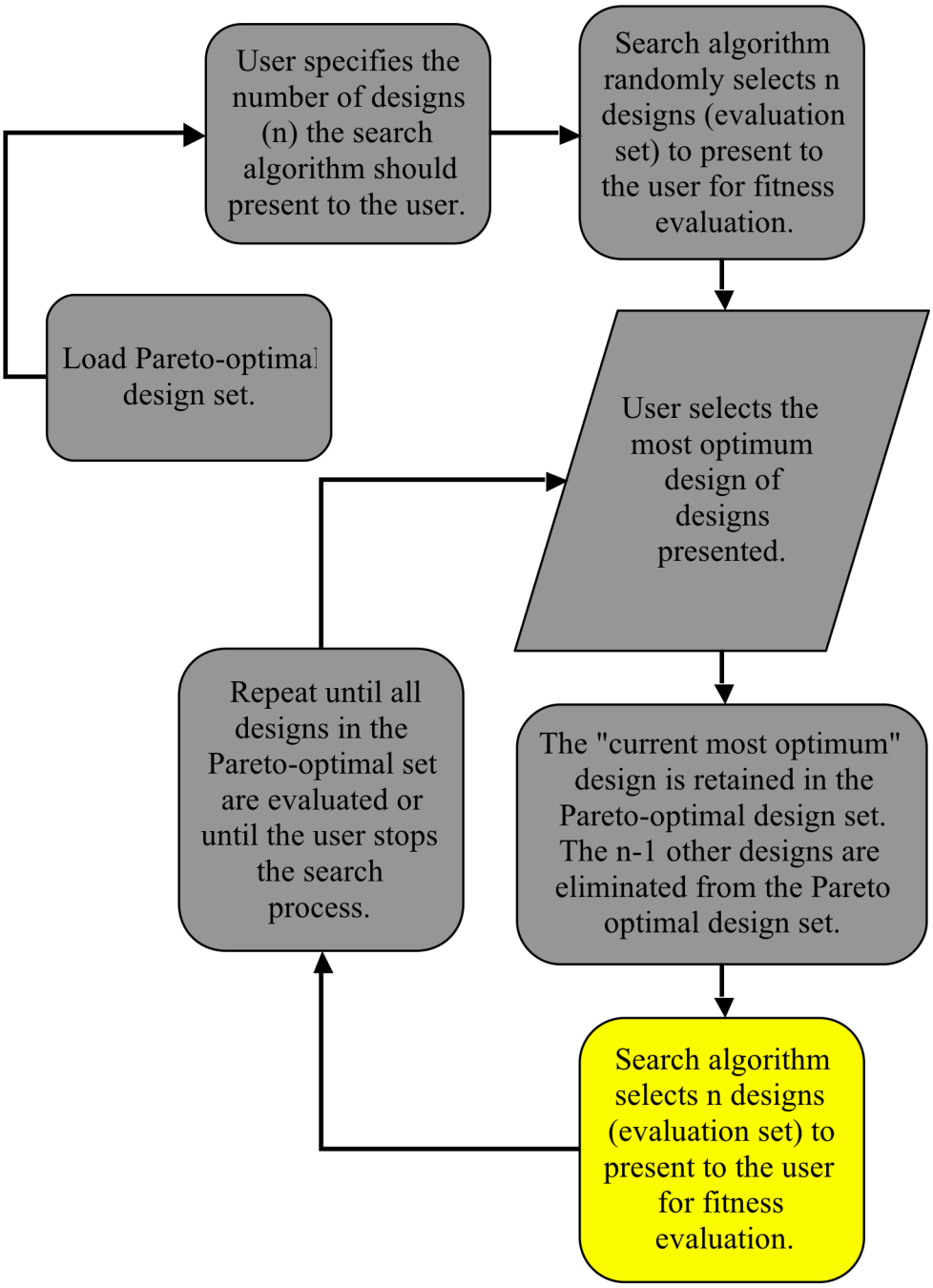

Figure 30: Level-2 optimization method.

The Level-2 optimization method has been developed with two different search

algorithms. The first algorithm is a random walk algorithm. This algorithm searches the Pareto-optimal design solution set by choosing the *n* design solutions for the evaluation set randomly from the Pareto-optimal design solution set. In the literature this is often referred to as a random walk algorithm because the path taken to the optimum solution is chosen in a random manner.

The second search algorithm is a Min/Max search algorithm. This algorithm searches the Pareto-optimal design solution set by choosing the evaluation set from the Pareto-optimal design solution set in the following manner:

- one design solution is chosen at random
- one design solution is chosen that is the maximum Euclidian distance in the design variable space from the current optimum design solution
- one design is chosen that is the minimum Euclidian distance in the design variable space from the current optimum design
- the current optimum design is retained

The Euclidian distance between two points is calculated according to Equation 24 (Stewart, J. 1998).

The Level-2 optimization software is built in the C++ computer language.

$$|\mathbf{p},\mathbf{q}| = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \ldots + (q_n - p_n)^2}$$
$$\mathbf{p} = (p_1, p_2, p_n)$$
$$\mathbf{q} = (q_1, q_2, q_n)$$

Equation 24: Euclidian distance between two points.

The method used in this thesis to solve the problem of *integrating CFD models earlier in the PDP to facilitate engineering decision making early in the PDP* builds on known techniques as well as developed new search algorithms. The software framework for finding the Pareto-optimal design solution set uses commercially available CAD software, CFD software, multi-objective optimization algorithms, and simulation workflow execution engine as well as a unique Level-2 optimization framework with multiple search algorithms. These various software packages are connected together in a manner that allow their application to general internal flow engineering devices. The results shown in CHAPTER 6 show that the method presented in this thesis has achieved the goal of integrating CFD earlier in the PDP to facilitate engineering decision making.

CHAPTER 6 : RESULTS AND DISCUSSION

This chapter presents the results of the method presented in this thesis as applied to the three example problems outlined in CHAPTER 1.

6.1 Example Case 1

Case 1 demonstrates the design of a tube and fin, liquid to air heat exchanger fin that maximizes the heat transfer from the liquid to the air with the minimum air side pressure drop. Kays, W., M., London, L., A. (1984) illustrates the function and various design and performance considerations for liquid to air heat exchangers.

Figure 31 shows a representative tube and fin arrangement of a tube and fin heat exchanger. The liquid flows through the tube and the air flows through the passage created by the fin and tube walls. The heat flows from the liquid to the tube, then to the fin, and finally to the air. A heat exchanger is composed of many fins and tubes soldered together with a top and bottom plate and associated liquid tanks. For this study, a single air passage is studied.

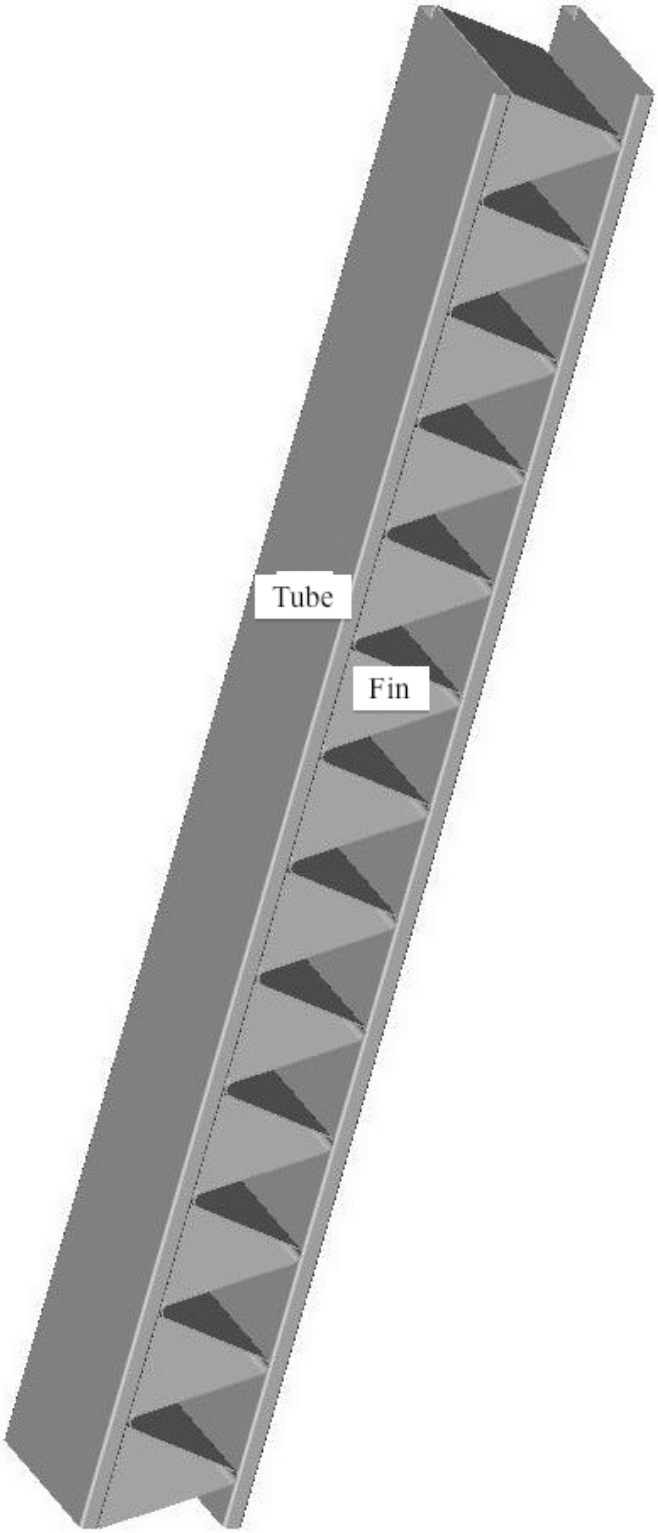

Figure 31: Case 1 fin design problem.

Figure 32 shows the CFD domain that is created by the fin and tube passage including the pertinent design variables for this case, which are the radii and flat length of the fin.

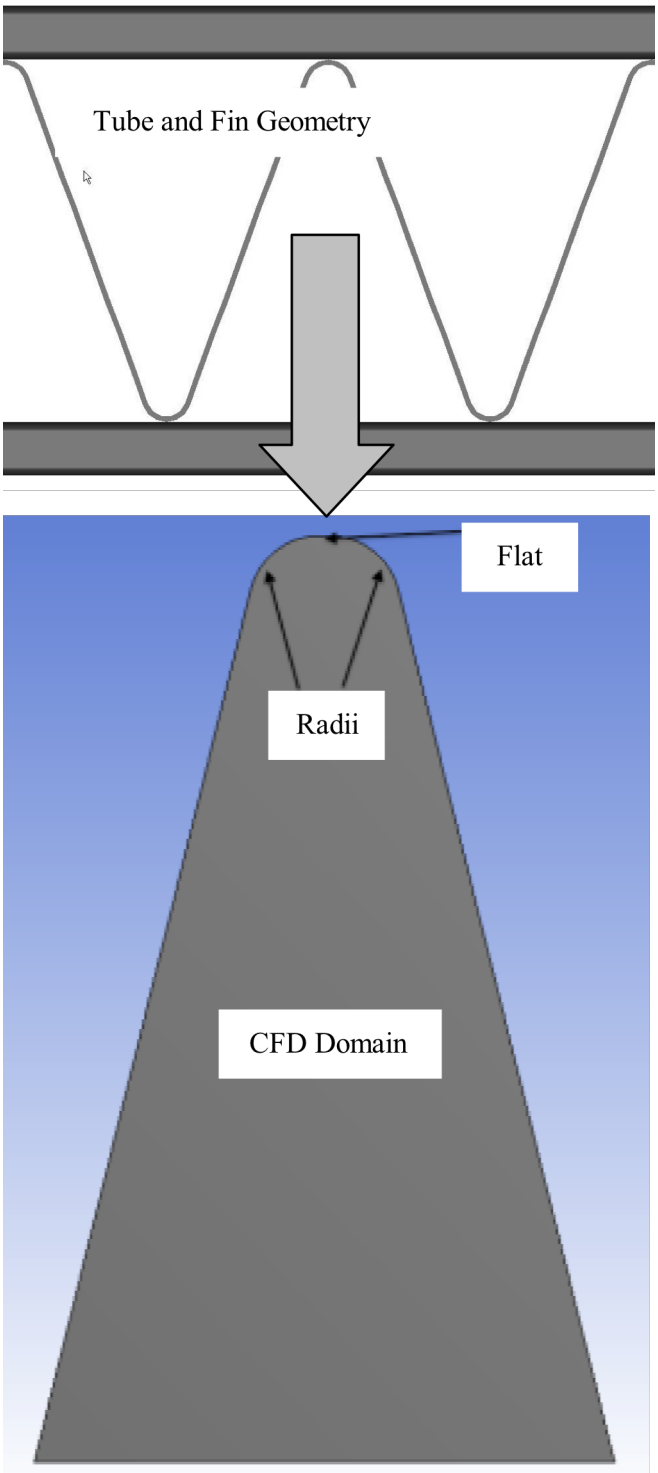

Figure 32: Case 1 design variables.

Figure 33 shows a represented CFD mesh for one of the design solutions evaluated. The mesh has the characteristics of being a structured, hexagonal dominant mesh. A second order accurate discretization scheme and double precision Reynolds Averaged Navier-Stokes (RANS) solver is used. The flow medium is represented as an incompressible, ideal gas. The realizable κ-ε turbulence model is used with standard wall functions.

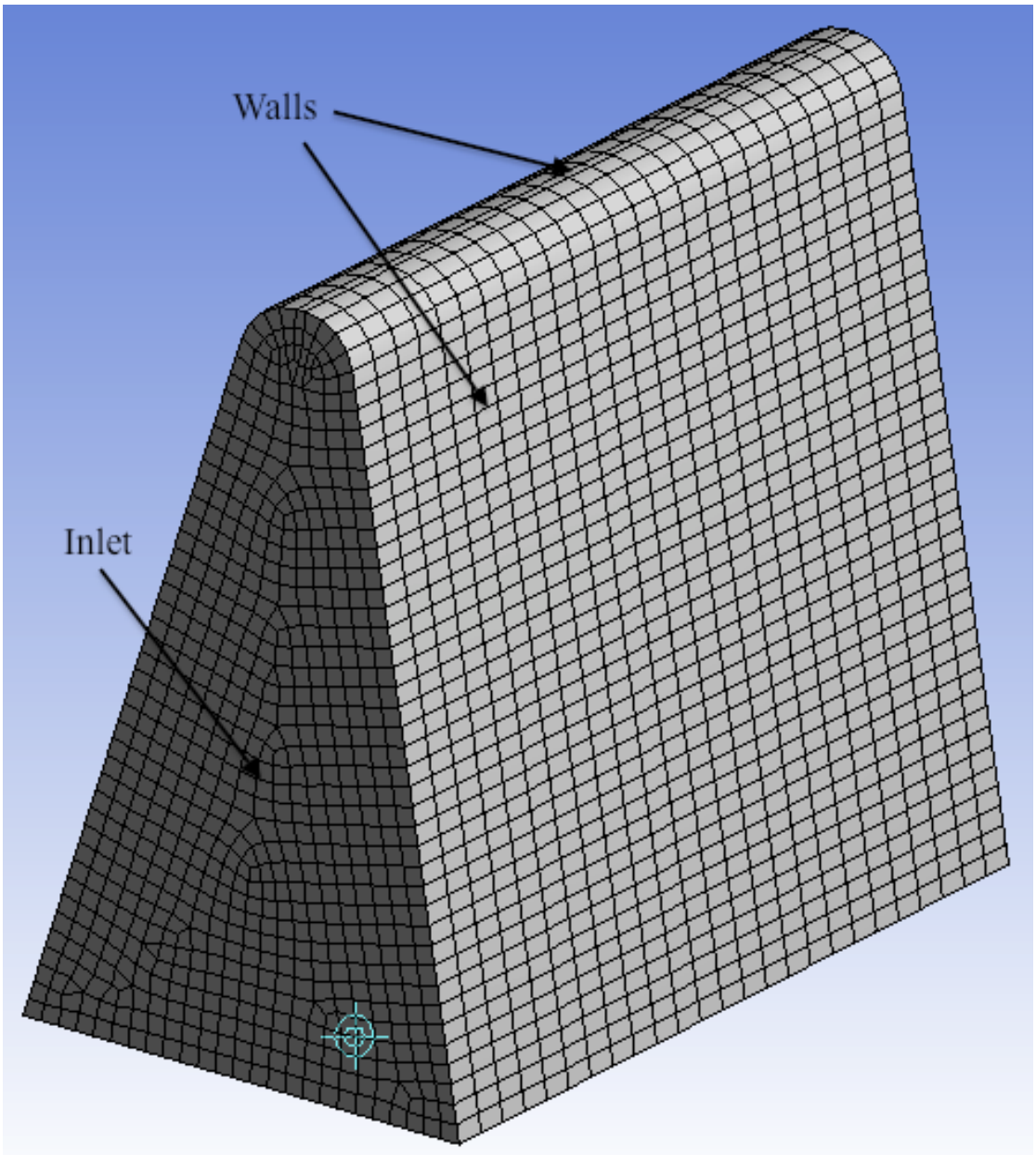

Figure 33: Mesh of a typical fin passage used in case 1.

Table 5 shows the boundary conditions for this case. It is assumed that the

temperature gradient in the fin and tube wall as well as the contact resistance between the fin and tube is negligible and as such is not included in the CFD model.

Table 5: Case 1 CFD model boundary conditions.

Boundary Condition	Units	Value
Inlet Velocity	m/s	10
Inlet Temperature	C	25
Wall Temperature	C	100
Outlet Pressure	kPa	100

The CFD model runs in approximately 2.5 minutes, which allows the Level-1 multi-objective optimizer to use the CFD model directly to evaluate the design solutions. This case uses the simulation workflow shown in Figure 34, with the appropriate CAD model, meshing parameters, and CFD solver settings as well as the appropriate design variables and objectives. To solve this design problem, Pro/ENGINEER® was used to generate a CAD representation of the CFD domain of the air passage. ANSYS® mesher and ANSYS® FLUENT™ within ANSYS® Workbench™ were the mesh generation software and CFD solver that were used, respectively, to perform the CFD calculations to generate the pressure drop values and wall heat flux for the various combinations of the design variables shown in Table 6.

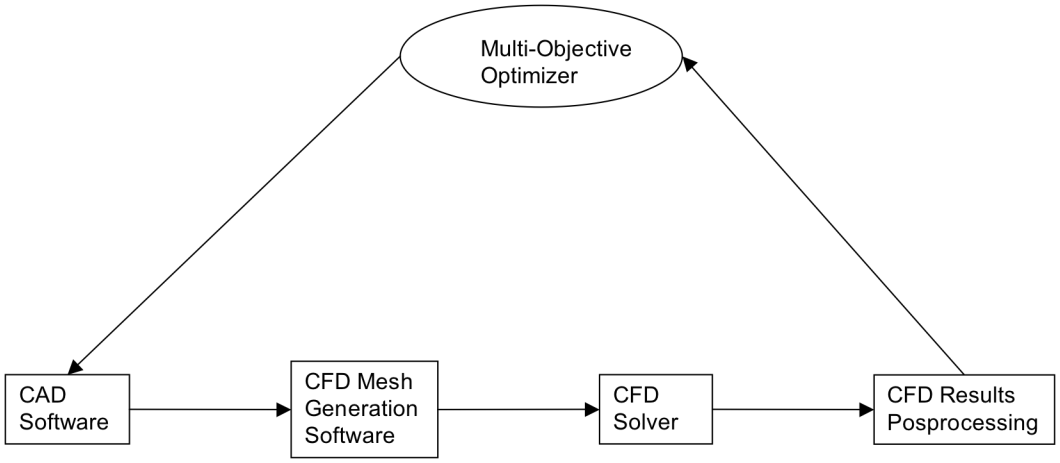

Figure 34: Case 1 simulation workflow.

Table 6: Case 1 design variables.

Design Variable	Units	Minimum	Maximum
Flat	m	0.0001	0.004
Radii	m	0.0005	0.0024

Figure 35 shows the Pareto-optimal design set as well as multiple potential optimal design solutions. The multiple potential optimum design solutions were arrived at with the Min/Max search algorithm in the Level-2 optimization algorithm. As shown in Figure 35, the starting design is located significantly off of the Pareto-optimal design solution set (Pareto-front).

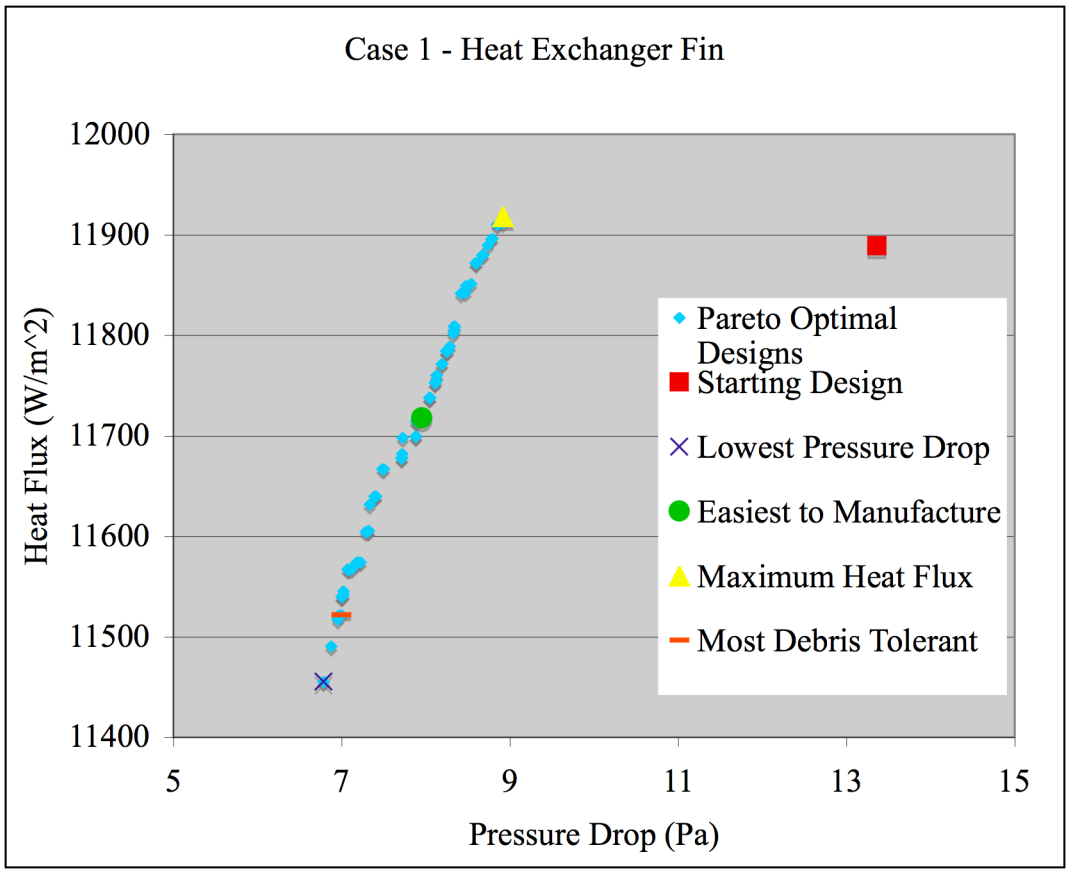

Figure 35: Pareto-optimal design solution set, starting design, and multiple potential optimum design solutions.

The Pareto-optimal design solution set includes 37 unique design solutions that required 16 hours to generate. As the Level-2 optimization algorithm with the random walk search algorithm was run, design solutions that were best suited to the higher-level information of manufacturing and debris tolerance were selected. The decisions that are made during the Level-2 optimization are assured to be optimum decisions because the design solutions are based on the Pareto-optimal design solution set. Figure 36 shows a CAD representation of each of the optimum design points shown in Figure 35.

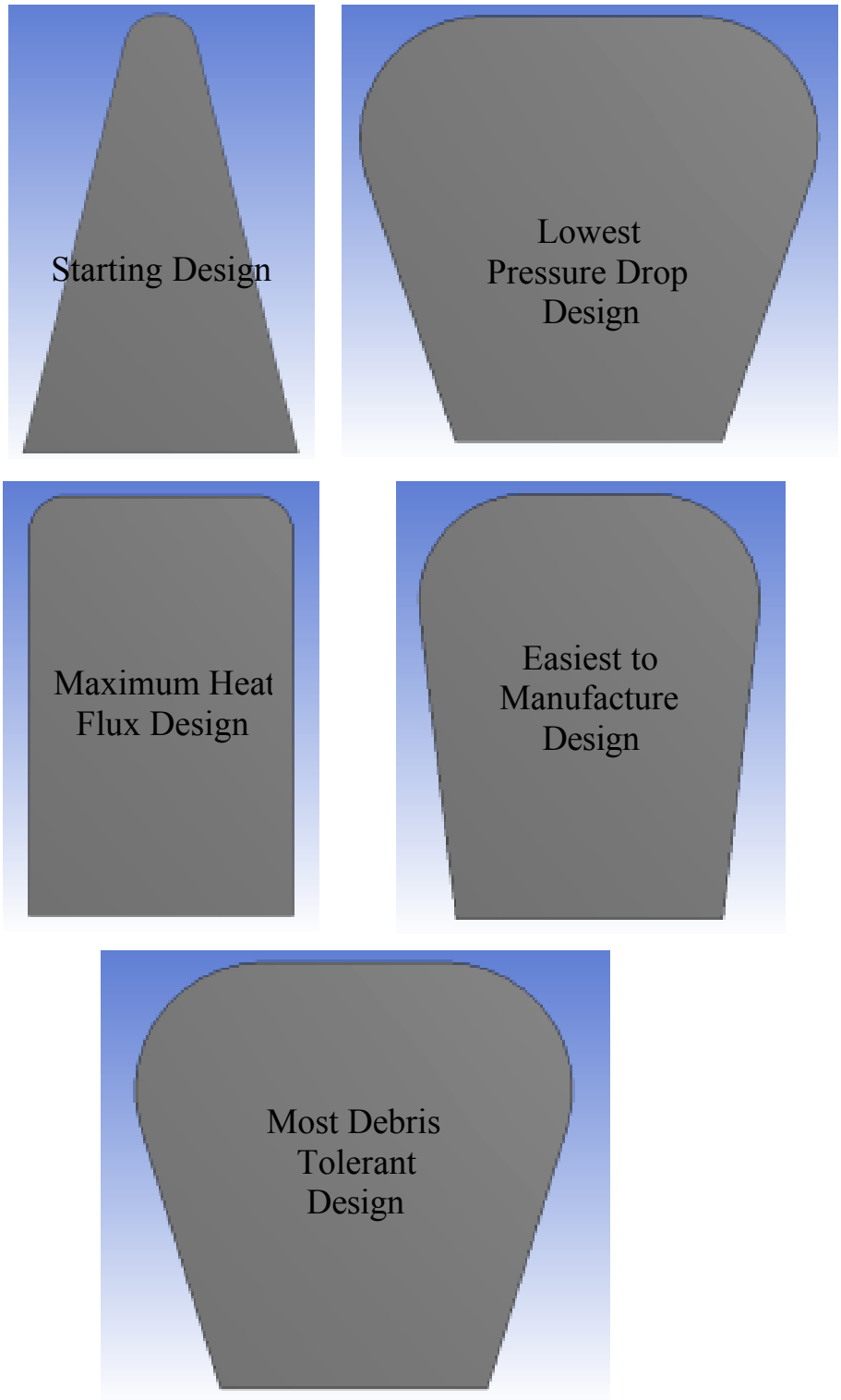

Figure 36: CAD representation of the starting design and multiple optimum design points.

This case shows the utility of the framework presented in this thesis. The Level-1 optimization algorithm determines what the Pareto-optimal design solution set is. During the Level-2 optimization, the algorithm uses the Pareto-optimal design solution set as input, which assures that the Level-2 optimization occurs on optimal design solutions.

6.2Example Case 2

Case 2 is the design of a jet pump that is used to induce a secondary flow by passing a primary flow through a nozzle that is immersed in a larger pipe as shown in Figure 37.

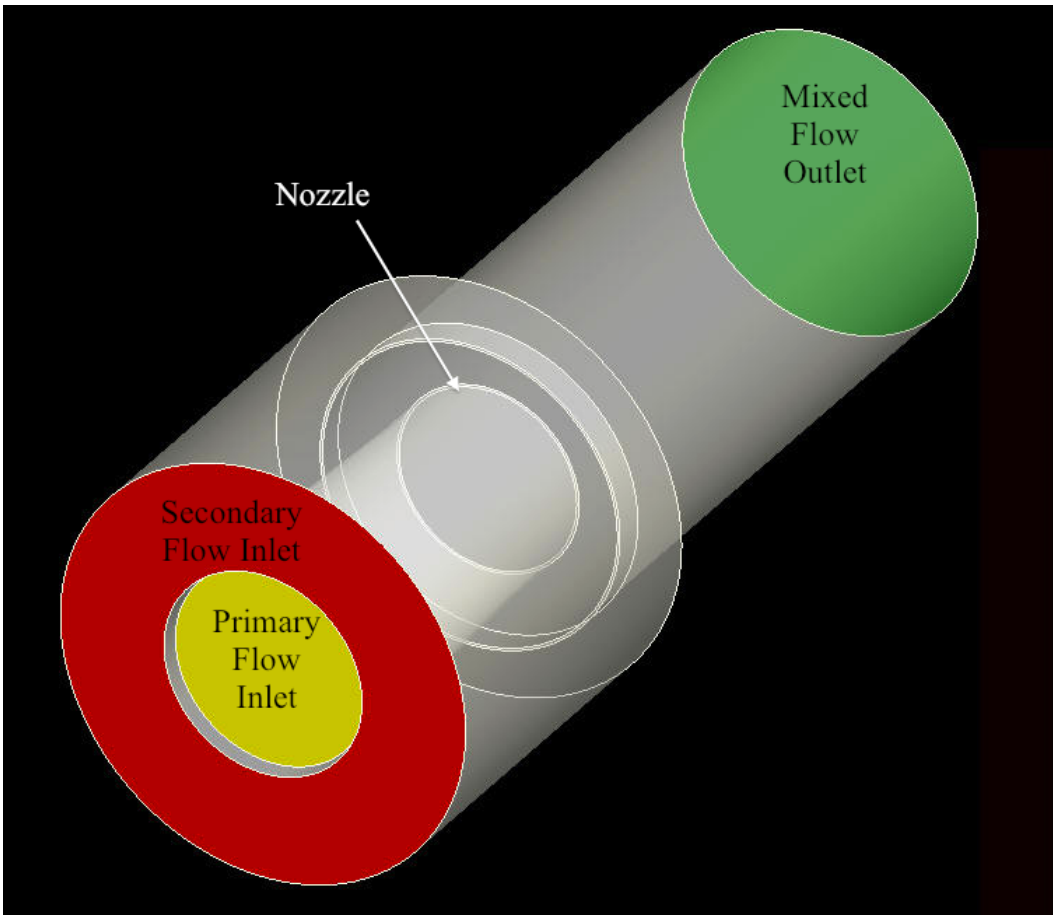

Figure 37: Case 2 jet pump design problem.

The design problem is to develop a jet pump that minimizes the total pressure drop between the mixed flow outlet and the primary flow inlet while maximizing the mass flow into the system through the secondary flow inlet. Jet pumps have been used in various applications similar to this as shown in Priestman, G. H., Tipetts, J. R. (1995), Long X., Yan H., Zhang S., Yao X. (2010), Beithou N., Aybar H. S. (2001), Fairuzov Y., Bredikhin V. (1995), Lorra M. A., Smith, J., Bussman W., Webster, T. (2001). Figure 38

shows the design variables that are changed in this case and Table 7 shows the boundary conditions for the CFD model.

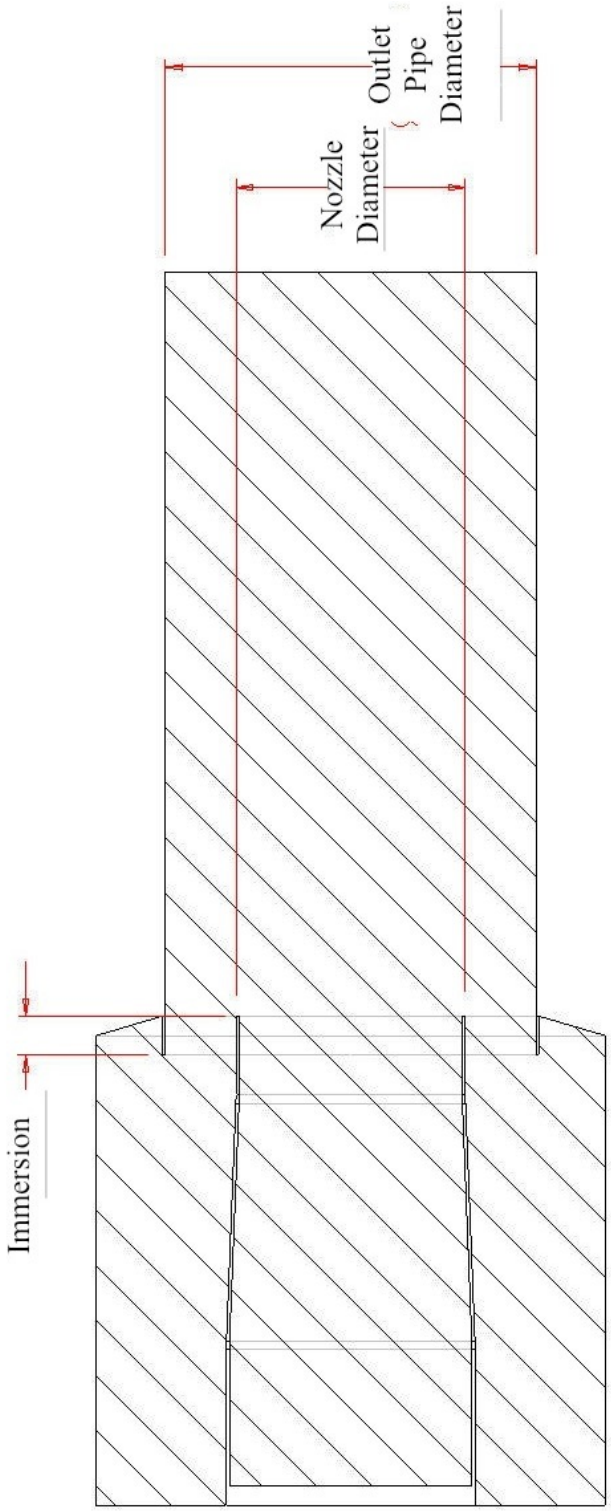

Figure 38: Case 2 design variables.

Table 7: Case 2 CFD model boundary conditions.

Boundary Condition	Units	Value
Primary Inlet Mass Flow Rate	kg/hr	1400
Primary Inlet Flow Temperature	C	650
Mixed Flow Outlet Pressure	kPa	100
Secondary Flow Inlet Pressure	kPa	100
Secondary Flow Inlet Temperature	C	120
Wall Heat Flux	w/m^2	0

To solve this design problem, Pro/ENGINEER® is used to generate a CAD representation of the CFD domain of the jet pump. ANSYS® mesher and ANSYS® FLUENT™ within ANSYS® Workbench™ were the mesh generation software, CFD solver and simulation execution engine that were used to perform the CFD calculations to generate the pressure drop values and secondary mass flow for the various combinations of the design variables shown in Table 8.

Table 8: Case 2 design variables.

Design Variable	Units	Minimum	Maximum
Immersion	m	0.01	0.02
Nozzle Diameter	m	0.072	0.092
Exhaust Pipe Diameter	m	0.114	0.134

Isight was used as the optimizer and the simulation workflow execution engine to perform the multi-objective Level-1 optimization. Figure 39 shows the entire simulation workflow for this case.

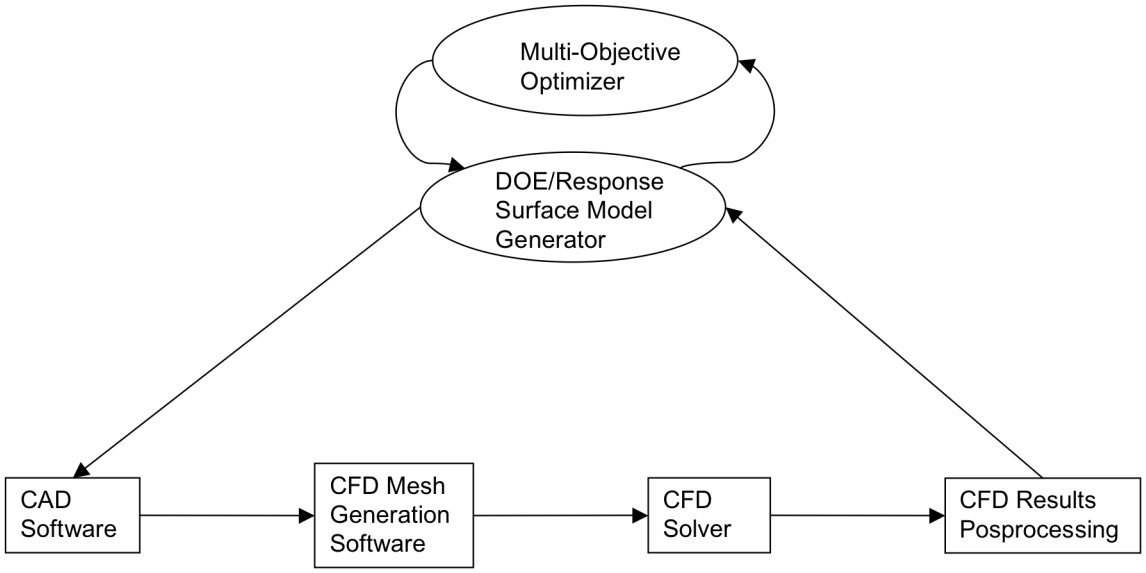

Figure 39: Case 2 and case 3 simulation workflow.

This CFD model requires approximately 0.5 hours to run one design case, which requires that a response surface model be generated and used by the Level-1 multi-objective optimizer, which is shown in Figure 40.

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Modify values of input parameters to compute new output values using Isight approximation.

Design Parameters	Values	Minimum	Maximum		Output Parameters	Values
P14 - immersion (m)	0.015	0.01	0.02		P19 - scavenge massflow (kg/s)	0.2155
P15 - nozzle radius (m)	0.041	0.036	0.046		P20 - pressure drop (pa)	2996
P16 - exhaust pipe radius (m)	0.062	0.057	0.067			

Figure 40: Case 2 response surface model interface.

Table 9 shows the three level, three factor central composite DOE that was used to sample the design space to generate the response surface model.

Table 9: Case 2 central composite DOE.

Row #	Immersion (m)	Nozzle Diameter (m)	Exhaust Pipe Diameter (m)
1	0.01	0.072	0.114
2	0.01	0.072	0.134
3	0.01	0.092	0.114
4	0.01	0.092	0.134
5	0.02	0.072	0.114
6	0.02	0.072	0.134
7	0.02	0.092	0.114
8	0.02	0.092	0.134
9	0.015	0.082	0.124
10	0.01	0.082	0.124
11	0.02	0.082	0.124
12	0.015	0.072	0.124
13	0.015	0.092	0.124
14	0.015	0.082	0.114
15	0.015	0.082	0.134

Figure 41 shows a representative CFD mesh for one of the design solutions evaluated. The mesh has the characteristics of being an unstructured tetrahedron mesh with 3 prism layers at all walls as shown in Figure 42. A second order accurate discretization scheme and double precision RANS solver is used. The flow medium is represented as an incompressible, ideal gas. The realizable κ-ε turbulence model is used with standard wall functions.

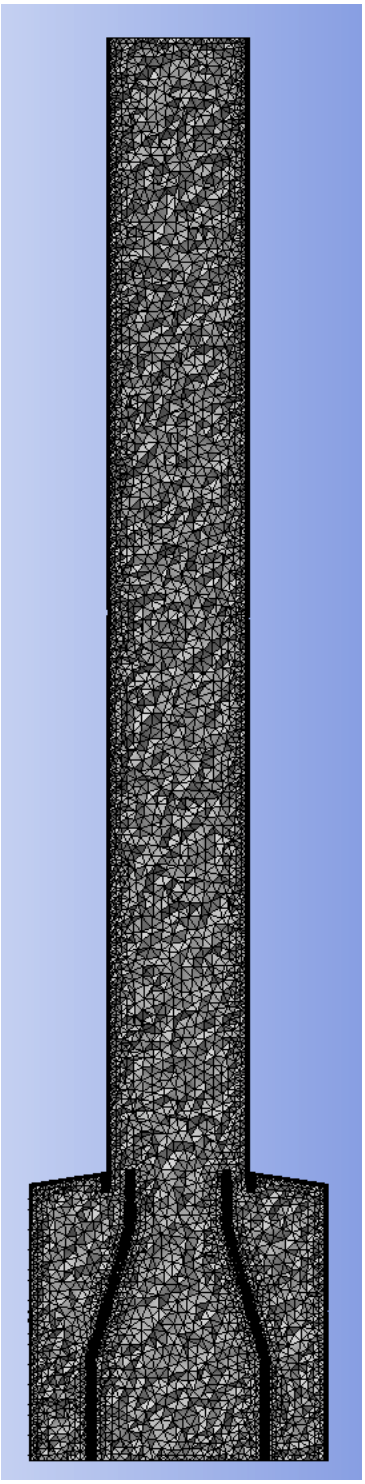

Figure 41: Overall section of a typical jet pump mesh used in case 2.

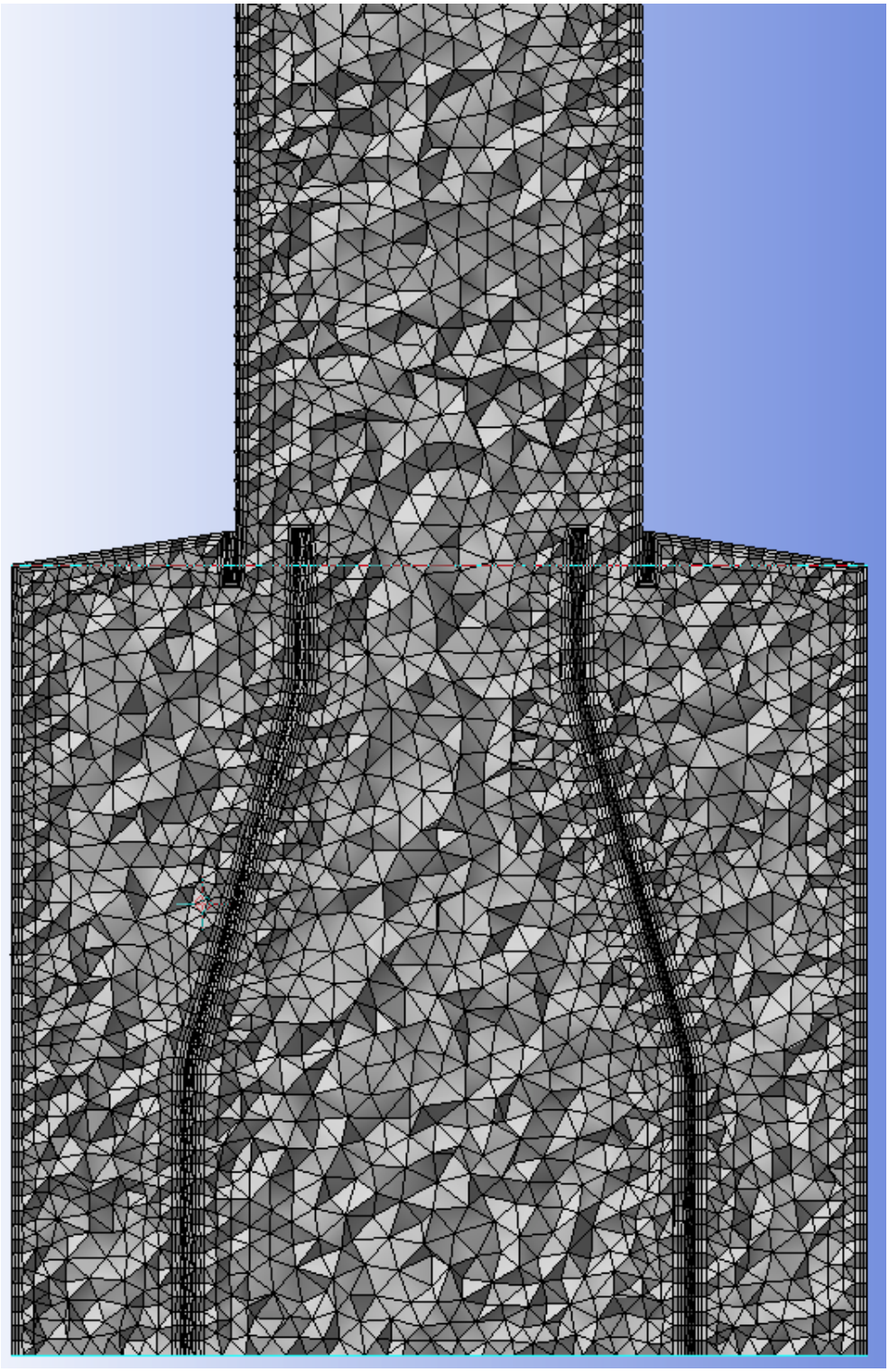

Figure 42: Detailed view of jet pump mesh, including prism layer mesh used in case 2.

The Level-1 optimization resulted in a Pareto-optimal design solution set that consisted of 126 optimal designs. In this case the engineer was seeking a single design that had less than 5000 Pa of pressure drop while having the highest possible induced mass flow. With these goals, the engineer ran the Level-2 optimization software twice; once with the random walk search algorithm and the second time with the Min/Max search algorithm. Figure 43 shows the Pareto-optimal design solution set in blue, the starting design in red, the optimum design arrived at when the random walk Level-2 optimization algorithm is used in yellow, and the optimum design arrived at when the Min/Max Level-2 optimization algorithm is used in green.

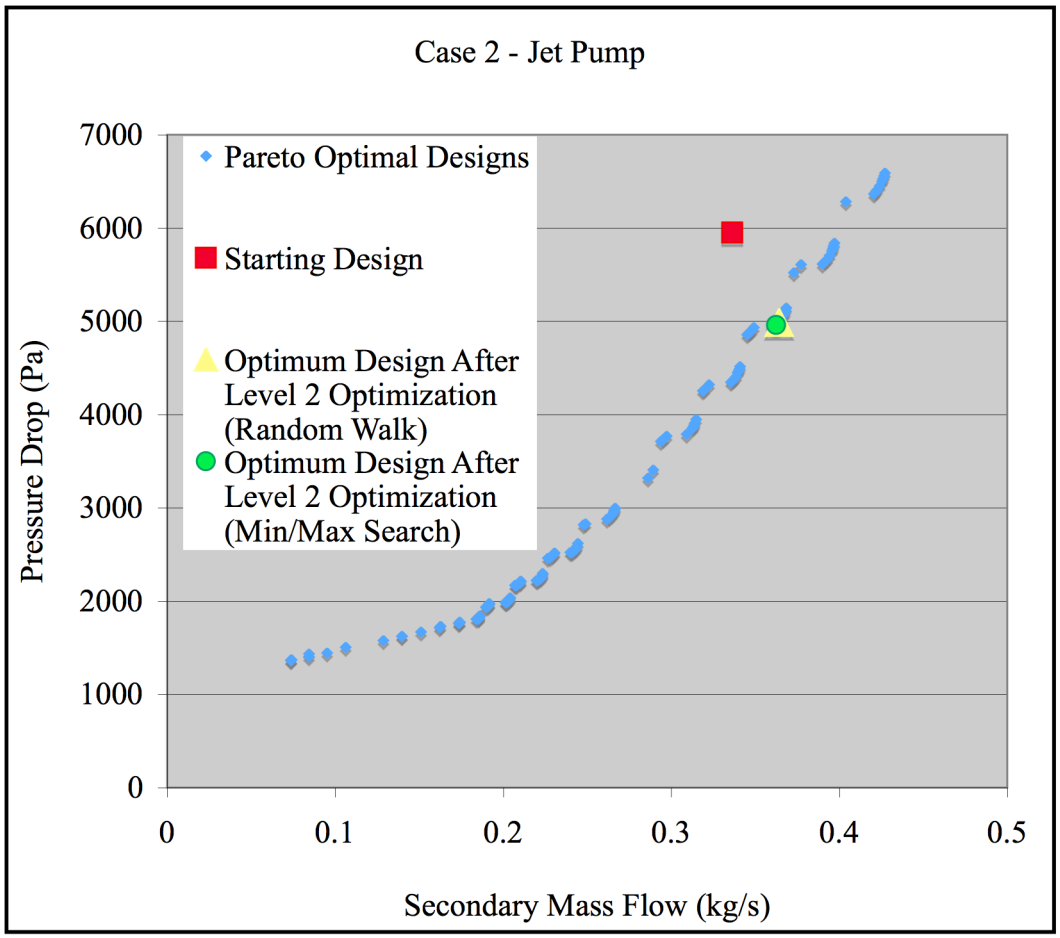

Figure 43: Case 2 Pareto-optimal design solutions, starting design solution, and selected optimum design solutions.

Table 10 shows the design variables, pressure drop, and induced mass flow for the starting design and two optimum designs.

Table 10: Case 2 design variables and design performance for starting design and optimum designs.

	Immersion (m)	Nozzle Diameter (m)	Exhaust Pipe Diameter (m)	Induced Mass Flow (kg/s)	Pressure Drop (Pa)
Starting Design	0.015	0.072	0.124	0.33613	5952
Optimum Design After Level 2 Optimization (Random Walk)	0.017	0.076	0.134	0.36415	4991
Optimum Design After Level 2 Optimization (Min/Max Search)	0.019	0.076	0.134	0.36245	4959

Figure 44 shows a plot of the velocity vectors at a plane located through the center of the computational mesh for the starting design. These plots illustrate how the fluid flows through the jet pump.

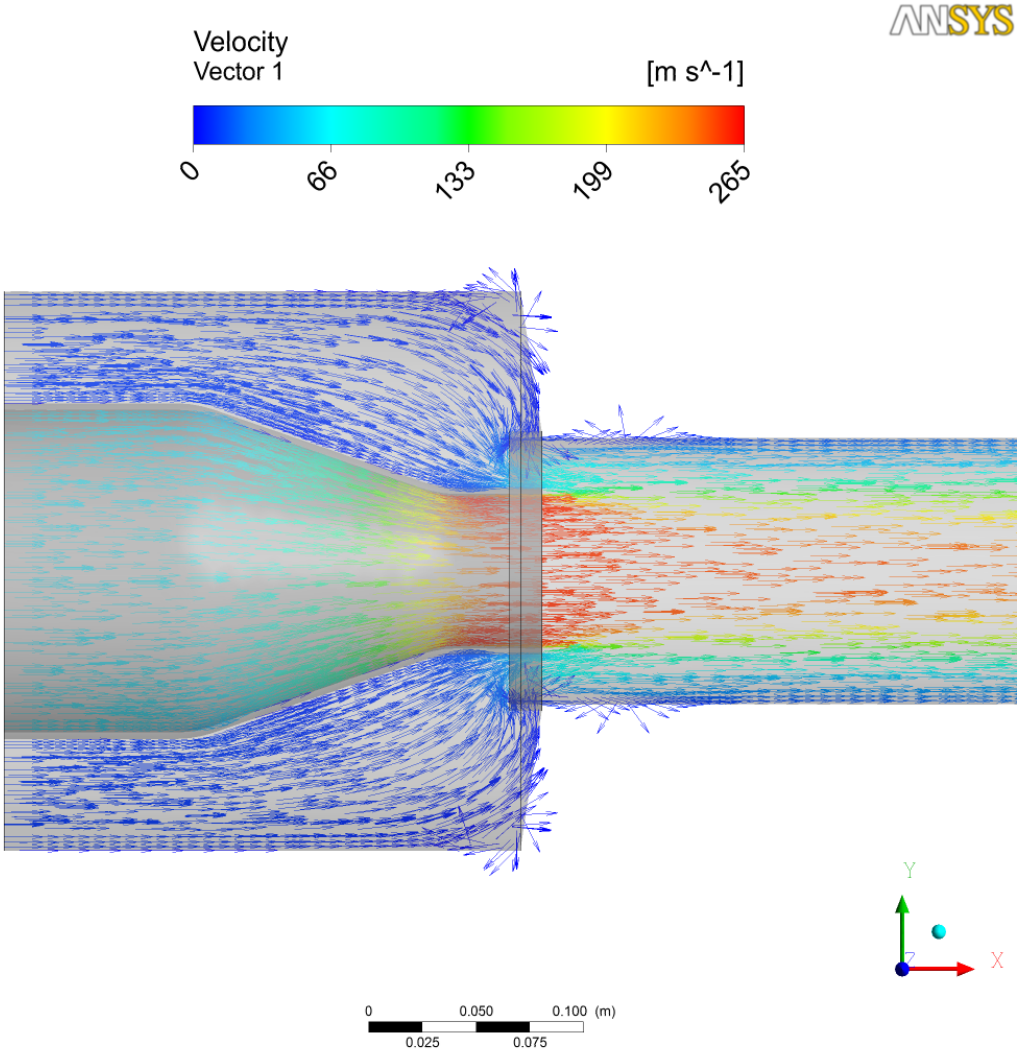

Figure 44: Case 2 starting design velocity vectors through the center of the CFD model.

The top plot in Figure 45 shows the velocity vectors through the center of the computational mesh for the optimum design arrived at when the random walk Level-2 search algorithm is used and the lower plot when the Min/Max Level-2 search algorithm is used.

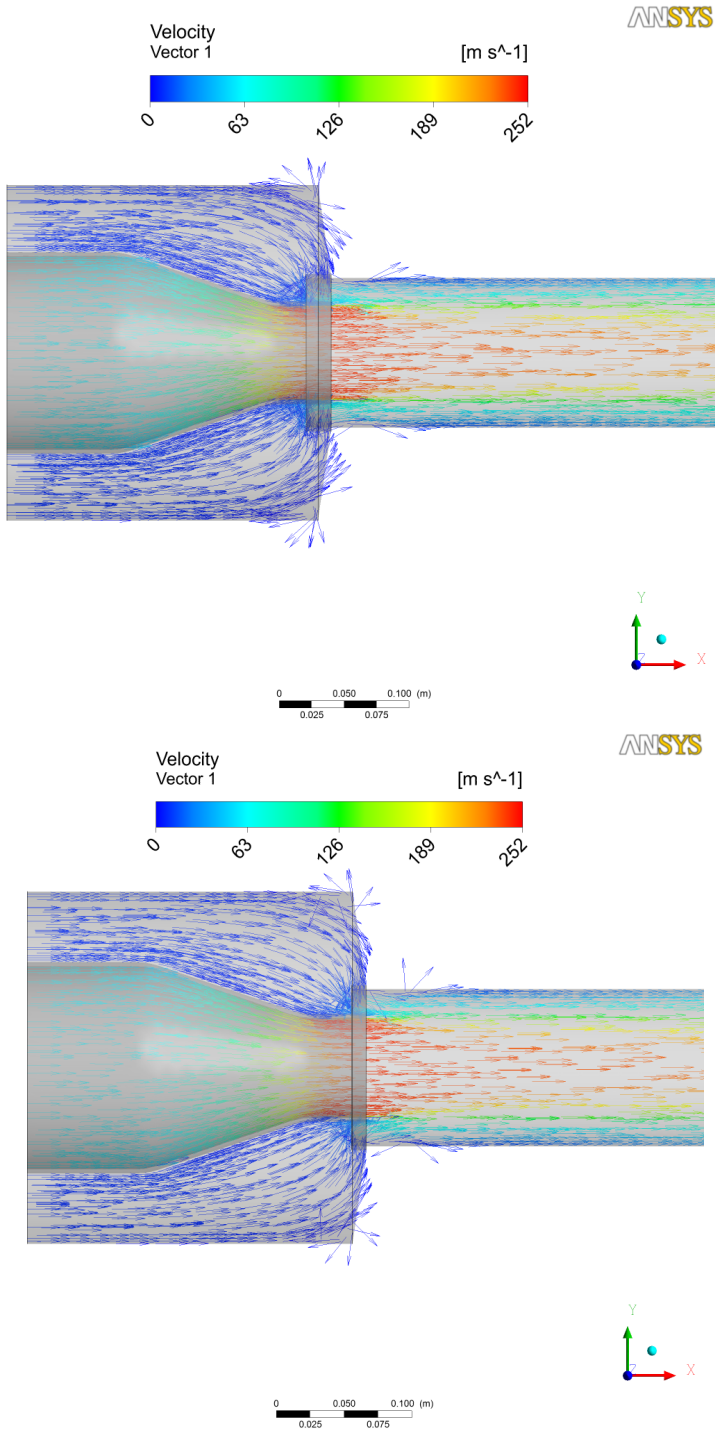

Figure 45: Case 2 velocity vectors through the center of the CFD model for the optimum designs. Upper plot for random walk search algorithm, lower plot for Min/Max search algorithm.

The results of this case show that the starting design solution is not optimum. The design solution arrived at with the random walk search algorithm has 8% more secondary mass flow and a 16% reduction is pressure drop. Similarly the design solution arrived at with the min/max search algorithm has 8% more secondary mass flow and a 17% reduction is pressure drop. In this case, the engineer was focused on finding optimum designs that had less than 5000 Pa in pressure drop with a maximum induced flow while having an exhaust pipe diameter that was not excessively large due to aesthetic requirements. This has driven a smaller nozzle diameter, more immersion, and a larger exhaust pipe diameter as a design solution.

The calculation time required to generate the response surface model was 7.75 hours, the generation of the Pareto-optimal design solution set required less than 1 minute, and the average Level-2 optimization required 10 minutes. This is significantly less than the 6 weeks that were required to arrive at the starting design when the traditional mechanical design approach is followed with CFD being used at the end of design process to determine how the design performed.

6.3 Example Case 3

Case 3 demonstrates the design of an inlet tank that maximizes the mass flow uniformity index at the tank outlet and minimizes the total pressure drop of the tank as shown in Figure 46. The design variables for this design problem are the inlet radius, perforated plate height, and the perforated plate hole diameters.

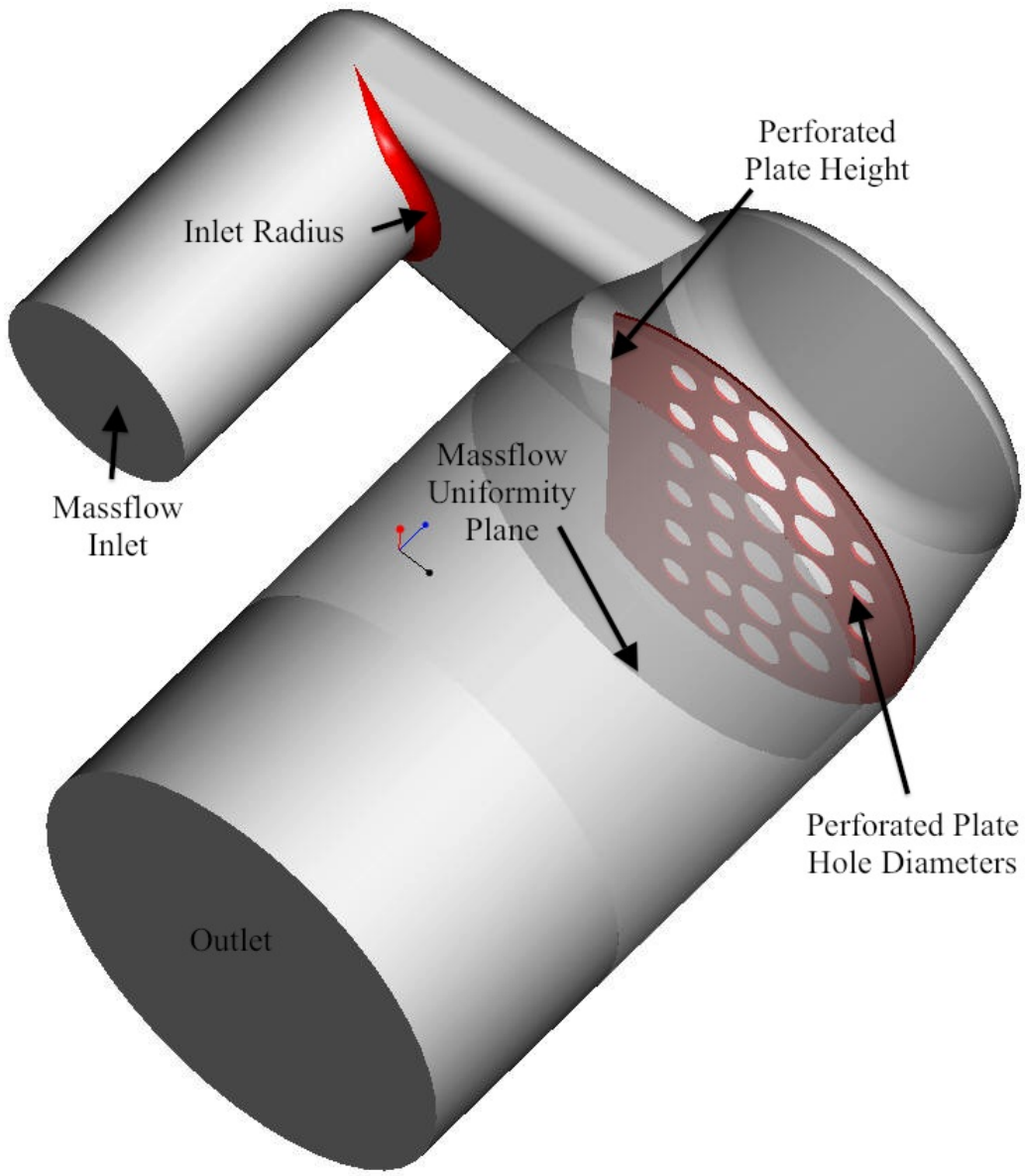

Figure 46: Case 3 inlet tank design problem.

The boundary conditions for this case are shown in Table 11.

Table 11: Case 3 CFD model boundary conditions.

Boundary Condition	Units	Value
Inlet Mass Flow Rate	kg/hr	1400
Inlet Temperature	C	650
Outlet Pressure	kPa	100
Wall Heat Flux	w/m^2	0

This case uses the same simulation workflow as case one shown in Figure 39, with the appropriate CAD model, meshing parameters, and CFD solver settings as well as the appropriate design variables and objectives. To solve this design problem Pro/ENGINEER® was used to generate a CAD representation of the inlet tank. ANSYS® mesher and ANSYS® FLUENT™ within ANSYS® Workbench™ were the mesh generation software, CFD solver and simulation execution engine that were used to perform the CFD calculations to generate the pressure drop values and mass flow uniformity index for the various combinations of the design variables shown in Table 12.

Table 12: Case 3 design variables.

Design Variable	Units	Minimum	Maximum
Row 1 & 2 Hole Diameter	m	0.01	0.02
Perforated Plate Height	m	0.19	0.22
Row 5 Hole Diameter	m	0.018	0.036
Row 3 & 4 Hole Diameter	m	0.015	0.03
Inlet Radius	m	0.01	0.05

This CFD model requires approximately 0.42 hours to run one design case, which requires that a response surface model be generated and used by the multi-objective optimizer, which is shown in Figure 47.

Adam J. Shuttleworth
18-Apr-11
Modify values of input parameters to compute new output values using RSM approximation.

Create Graph Data | Refresh Graph Data

Design Parameters	Values	Minimum	Maximum	Output Parameters	Values
Plate Height (mm)	190	190	220	Pressure Drop (Pa)	3674
Row 5 Hole Diam. (mm)	18	18	36	Velocity Unif. Index (-)	0.8328
Row 1 & 2 Hole Diam. (mm)	10	10	20		
Inlet Radius (mm)	10	10	50		
Row 3 & 4 Hole Diam. (mm)	15	15	30		

Figure 47: Case 3 response surface model interface.

Table 13 shows the three level, three factor central composite DOE that was used

to sample the design space to generate the response surface model.

Table 13: Case 3 central composite DOE.

Row #	Plate Height (m)	Row 5 Hole Diameter (m)	Row 1 & 2 Hole Diameter (m)	Inlet Radius (m)	Row 3 & 4 Hole Diameter (m)
1	0.190	0.018	0.010	0.010	0.0150
2	0.190	0.018	0.010	0.010	0.0300
3	0.190	0.018	0.010	0.050	0.0150
4	0.190	0.018	0.010	0.050	0.0300
5	0.190	0.018	0.020	0.010	0.0150
6	0.190	0.018	0.020	0.010	0.0300
7	0.190	0.018	0.020	0.050	0.0150
8	0.190	0.018	0.020	0.050	0.0300
9	0.190	0.036	0.010	0.010	0.0150
10	0.190	0.036	0.010	0.010	0.0300
11	0.190	0.036	0.010	0.050	0.0150
12	0.190	0.036	0.010	0.050	0.0300
13	0.190	0.036	0.020	0.010	0.0150
14	0.190	0.036	0.020	0.010	0.0300
15	0.190	0.036	0.020	0.050	0.0150
16	0.190	0.036	0.020	0.050	0.0300
17	0.220	0.018	0.010	0.010	0.0150
18	0.220	0.018	0.010	0.010	0.0300
19	0.220	0.018	0.010	0.050	0.0150
20	0.220	0.018	0.010	0.050	0.0300
21	0.220	0.018	0.020	0.010	0.0150
22	0.220	0.018	0.020	0.010	0.0300
23	0.220	0.018	0.020	0.050	0.0150
24	0.220	0.018	0.020	0.050	0.0300
25	0.220	0.036	0.010	0.010	0.0150
26	0.220	0.036	0.010	0.010	0.0300
27	0.220	0.036	0.010	0.050	0.0150
28	0.220	0.036	0.010	0.050	0.0300
29	0.220	0.036	0.020	0.010	0.0150
30	0.220	0.036	0.020	0.010	0.0300
31	0.220	0.036	0.020	0.050	0.0150
32	0.220	0.036	0.020	0.050	0.0300
33	0.205	0.027	0.015	0.030	0.0225
34	0.190	0.027	0.015	0.030	0.0225
35	0.220	0.027	0.015	0.030	0.0225
36	0.205	0.018	0.015	0.030	0.0225
37	0.205	0.036	0.015	0.030	0.0225
38	0.205	0.027	0.010	0.030	0.0225
39	0.205	0.027	0.020	0.030	0.0225
40	0.205	0.027	0.015	0.010	0.0225
41	0.205	0.027	0.015	0.050	0.0225
42	0.205	0.027	0.015	0.030	0.0150
43	0.205	0.027	0.015	0.030	0.0300

Figure 48 shows a representative CFD mesh for one of the design solutions evaluated. The mesh has the characteristics of being an unstructured tetrahedron mesh with 3 prism layers at all of the walls and a structured hexahedron mesh in the porous media, as shown in Figure 49. A second order accurate discretization scheme and double precision RANS solver is used. The flow medium is represented as an incompressible, ideal gas. The realizable κ-ε turbulence model is used with standard wall functions.

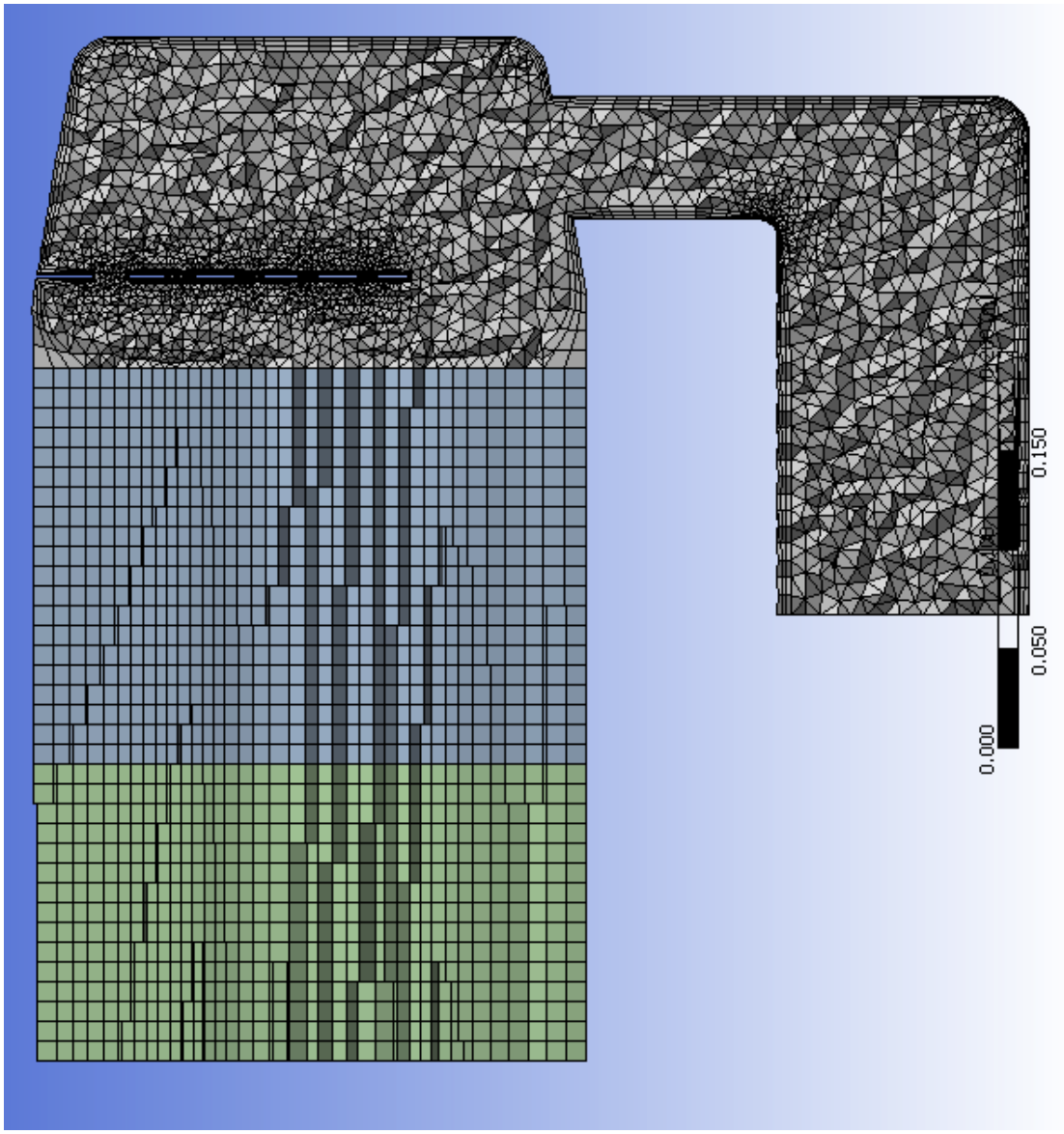

Figure 48: Overall section of a typical inlet tank mesh used in case 3.

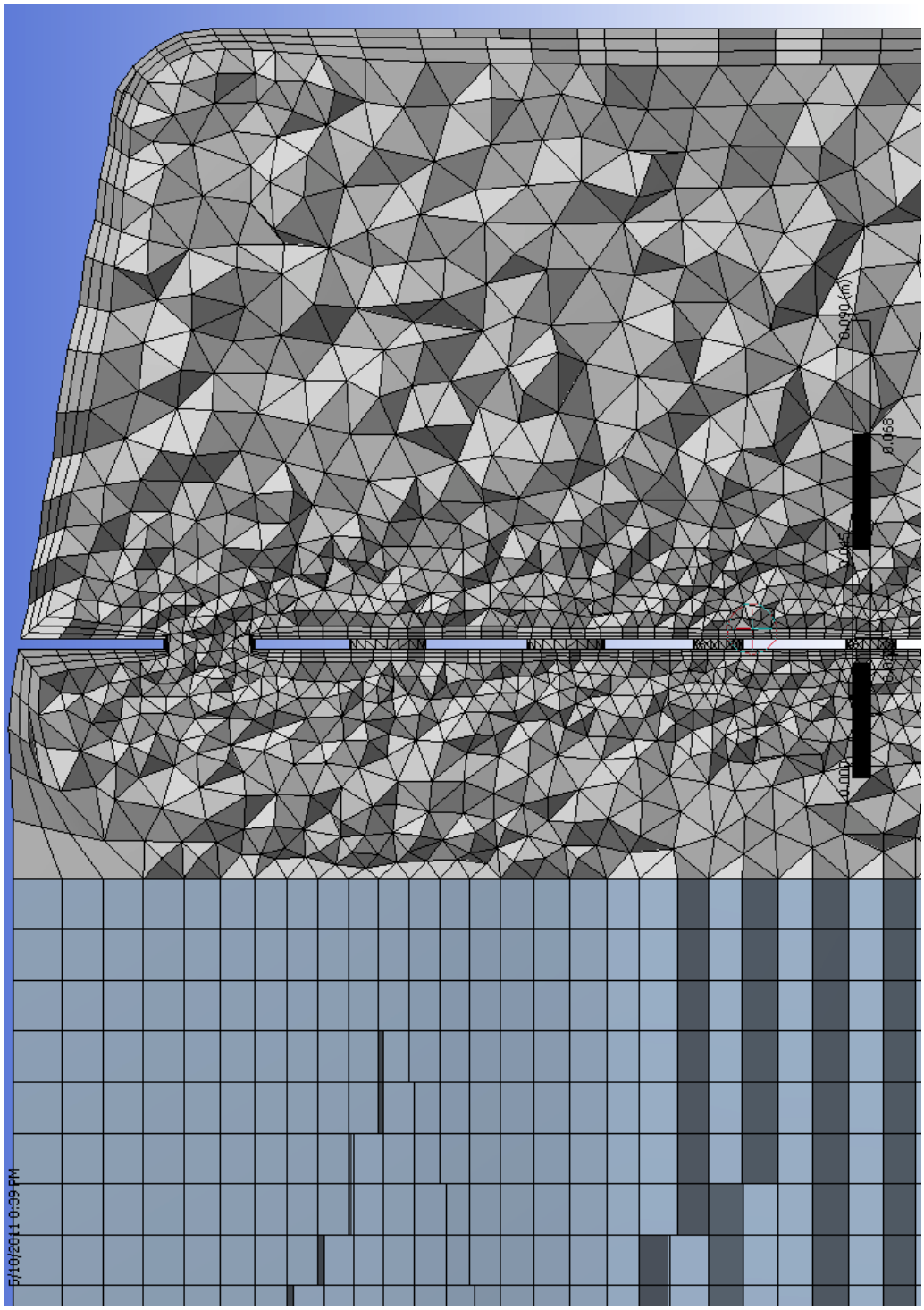

Figure 49: Detailed view of inlet tank mesh, including prism layer mesh used in case 3.

After the Level-1 optimization was complete the Pareto-optimal design set consisted of 67 optimal designs. In this case the engineer was seeking a single design that had less than 2600 Pa of pressure drop while having a mass flow uniformity index at the inlet tank exit plane greater than 0.85. With these goals, the engineer ran the Level-2 optimization software twice once with the random walk search algorithm and the second time with the Min/Max search algorithm. Figure 50 shows the Pareto-optimal design solution set in blue, the starting design in red, the optimum design arrived at when the random walk Level-2 search algorithm is used in yellow, and the optimum design arrived at when the min/max Level-2 search algorithm is used in green.

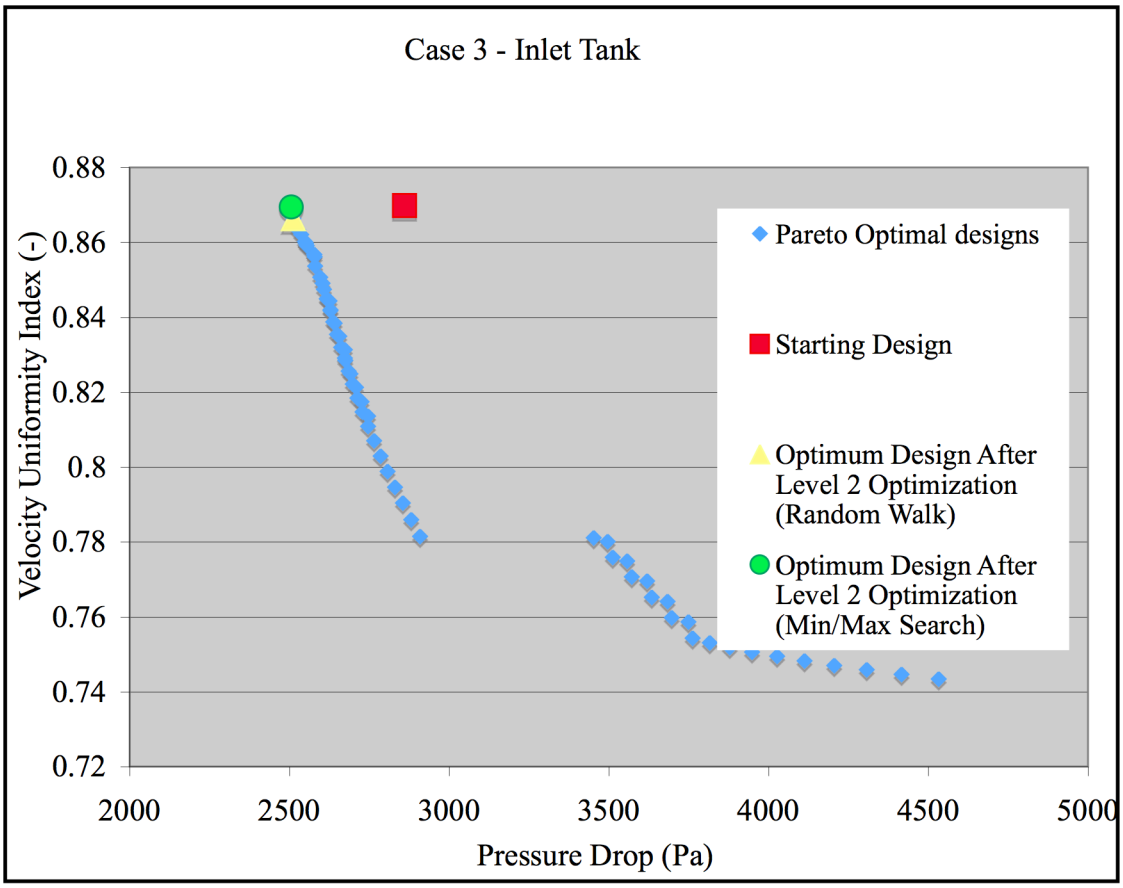

Figure 50: Case 3 Pareto-optimal design solutions, starting design solution, and selected optimum design solutions.

Table 14 shows the design variables, pressure drop, and mass flow uniformity index for the starting design and two optimum designs.

Table 14: Case 3 design variables and design performance for starting design and optimum designs.

	Plate Height (m)	Row 5 Hole Diameter (m)	Row 1 & 2 Hole Diameter (m)	Inlet Radius (m)	Row 3 & 4 Hole Diameter (m)	Pressure Drop (Pa)	Mass Flow Uniformity Index (-)
Starting Design	190	36	20	10	30	2860	0.8698
Optimum Design After Level 2 Optimization (Random Walk)	190	26	20	50	30	2512	0.8664
Optimum Design After Level 2 Optimization (Min/Max Search)	190	24	20	50	30	2506	0.8694

Figure 51, Figure 54, and Figure 57 show plots of streamlines seeded at the outlet boundary of the CFD domain for the starting design, the optimum design arrived at with the random walk Level-2 search algorithm, and the optimum design arrived at with the Min/Max Level-2 search algorithm respectively. Figure 52, Figure 55, and Figure 58 show plots of velocity vectors at a plane located at the center of the CFD domain for the starting design, the optimum design arrived at with the random walk Level-2 search algorithm, and the optimum design arrived at with the Min/Max Level-2 search algorithm respectively. Figure 53, Figure 56, and Figure 59 show plots of velocity contours at a plane located at the outlet of the inlet tank. These plots provide an illustration of the flow field for the starting design of the inlet tank and the optimum design arrived at with the random walk and Mix/Max Level-2 search algorithms.

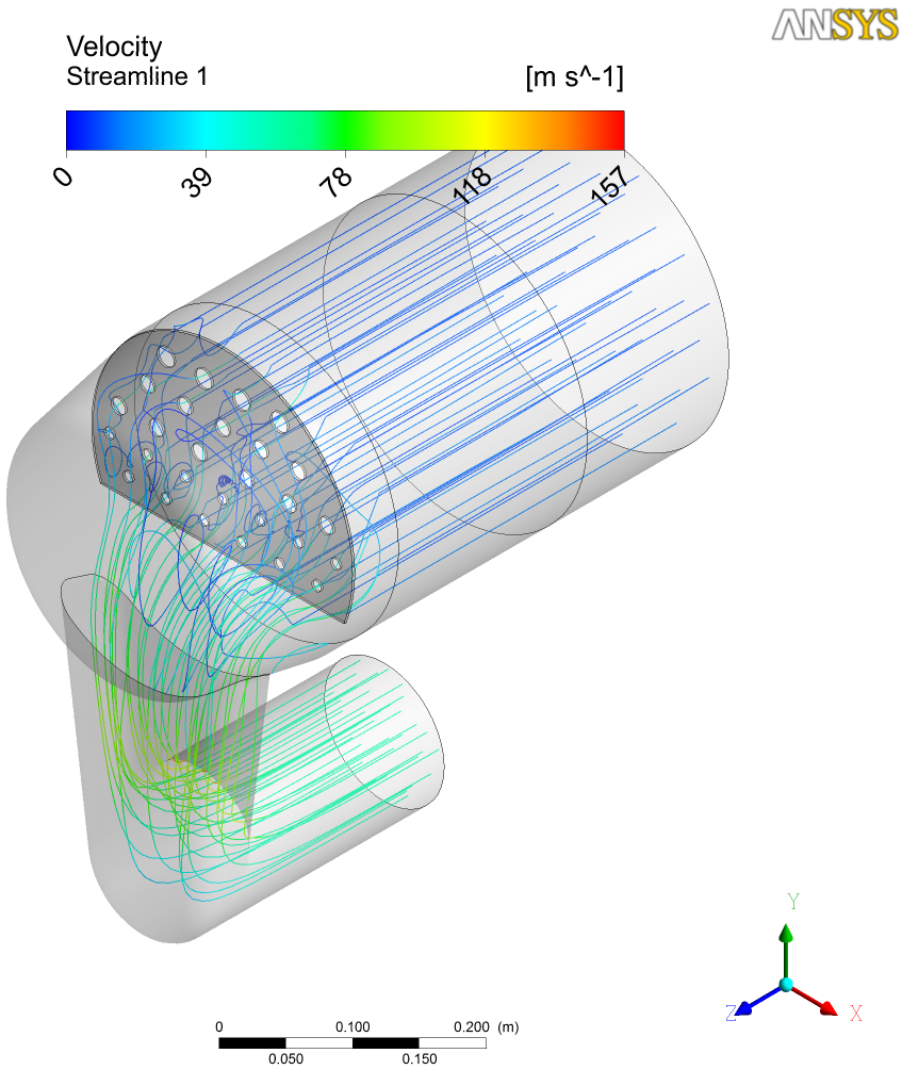

Figure 51: Case 3 starting design streamlines.

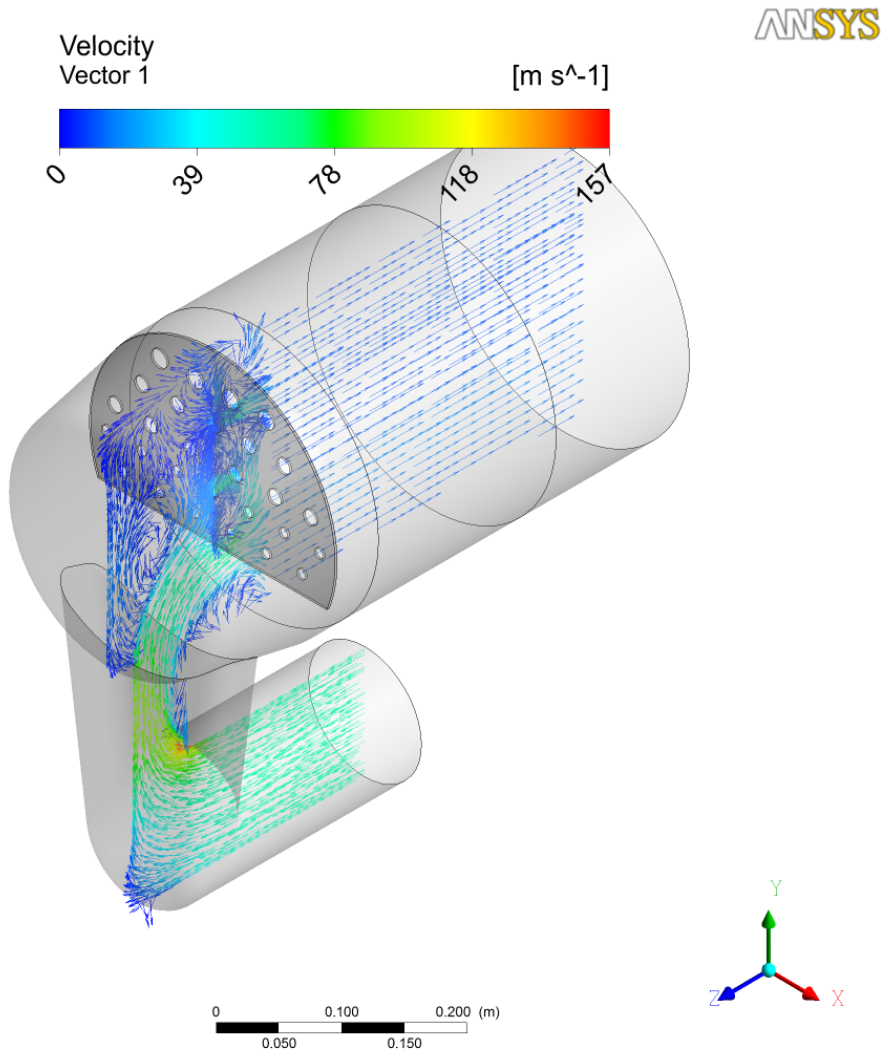

Figure 52: Case 3 starting design velocity vector plot on a plane located through the center of the CFD model.

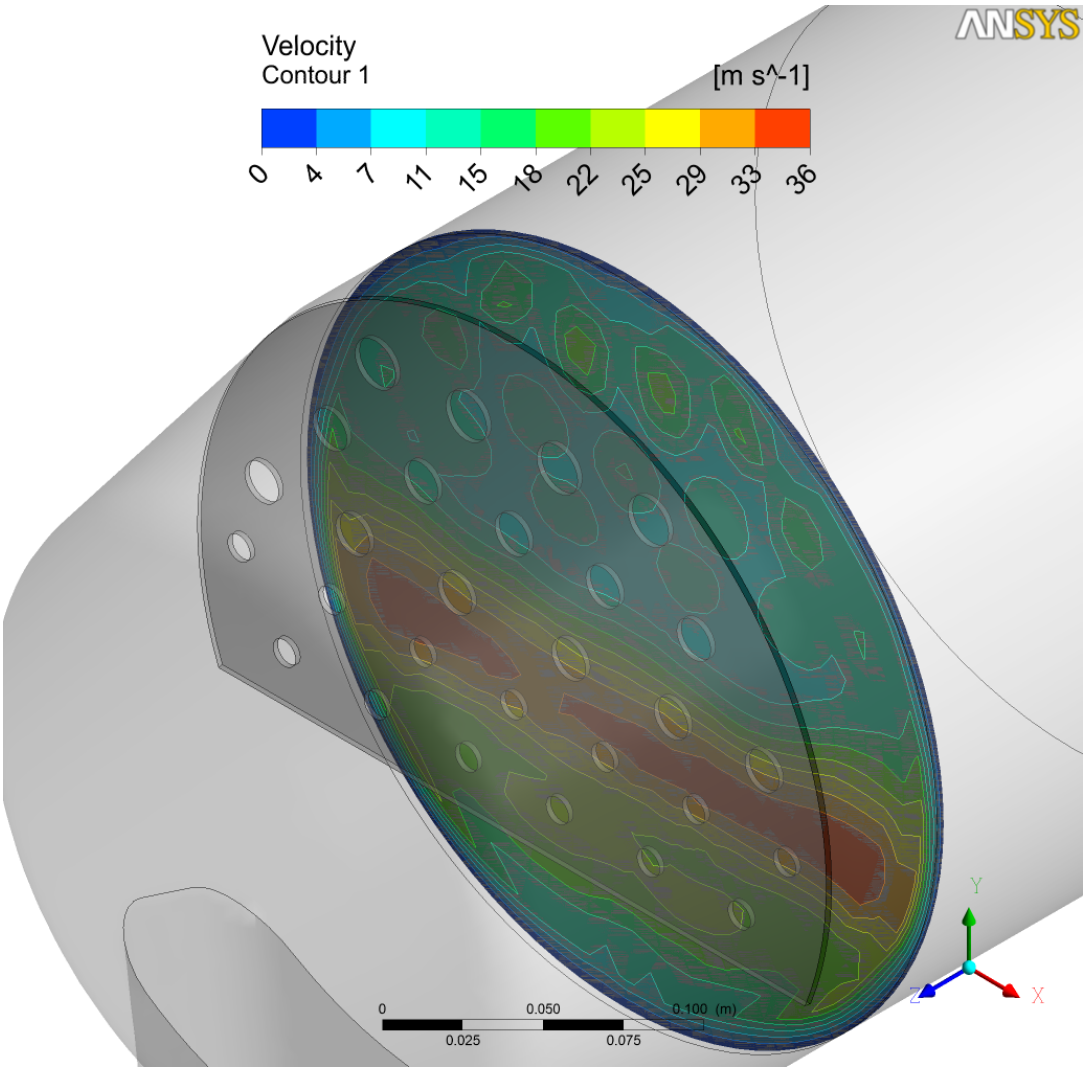

Figure 53: Case 3 starting design velocity contour plot on a plane located at the outlet of the inlet tank.

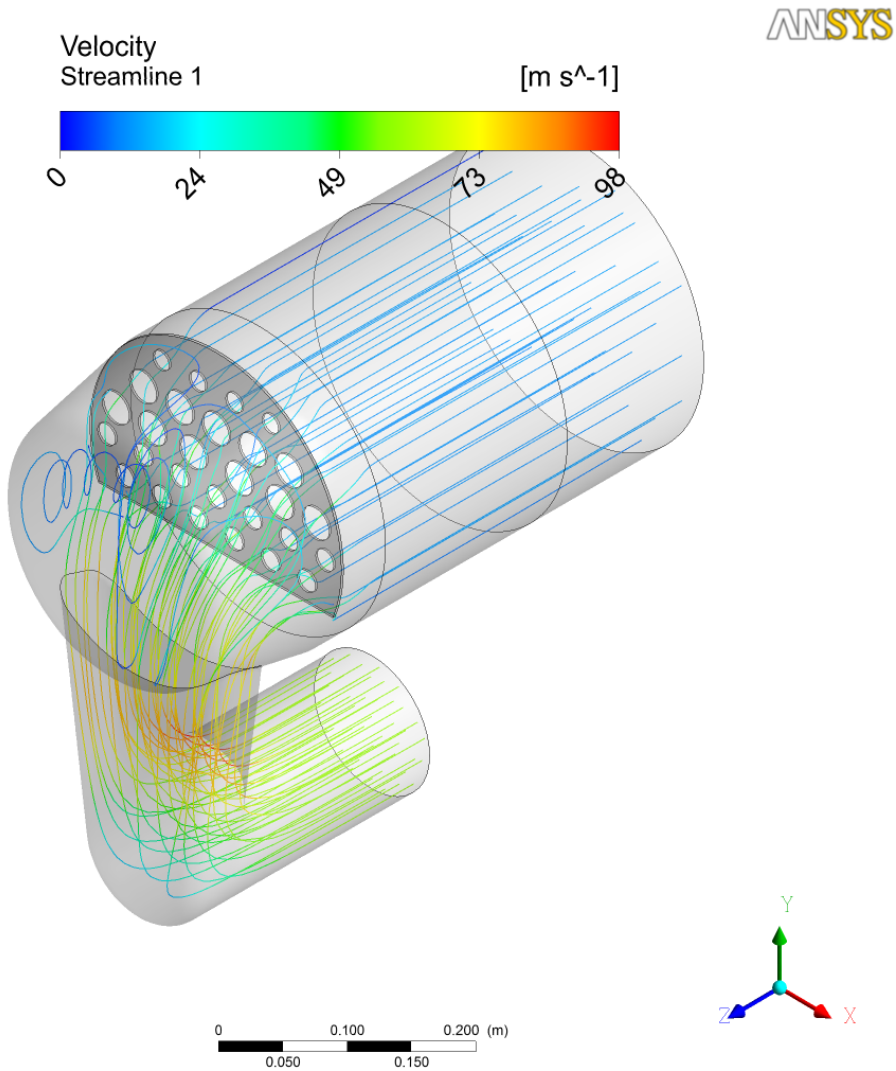

Figure 54: Case 3 streamlines in optimum design of the random walk Level-2 search algorithm.

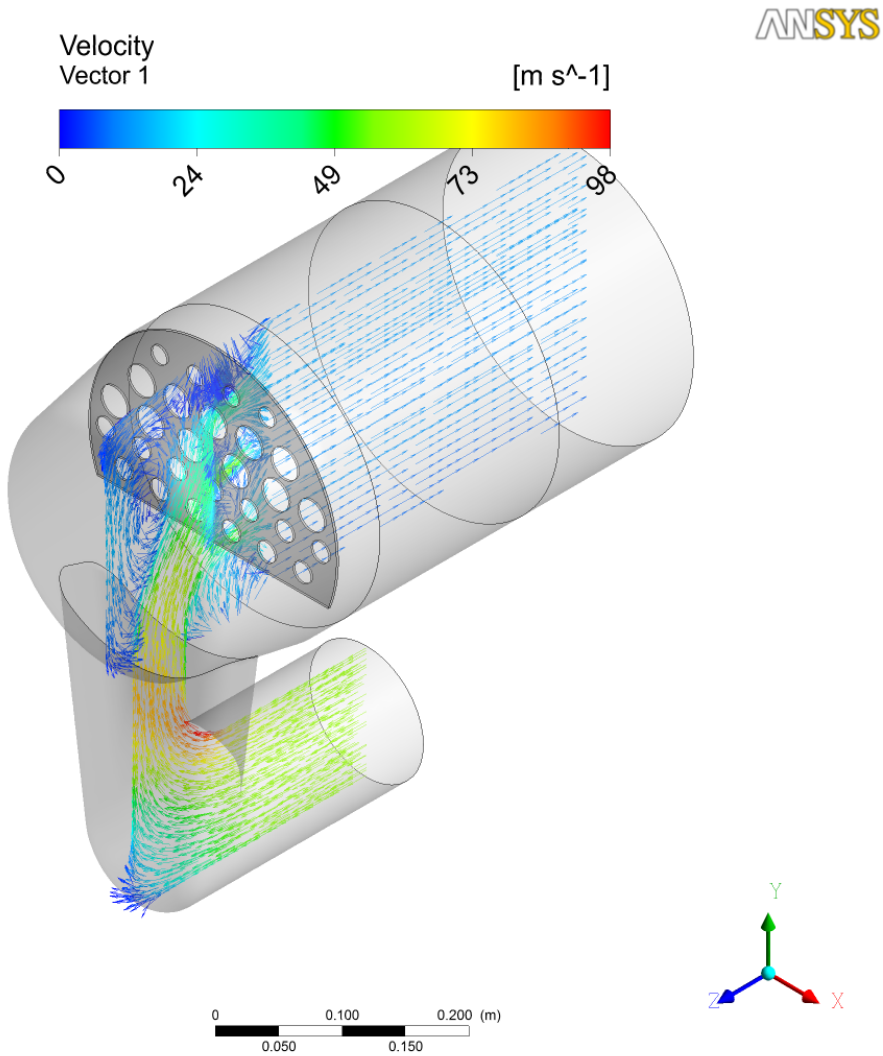

Figure 55: Case 3 velocity vector plot on a plane located through the center of the CFD model of the optimum design of the random walk Level-2 search algorithm.

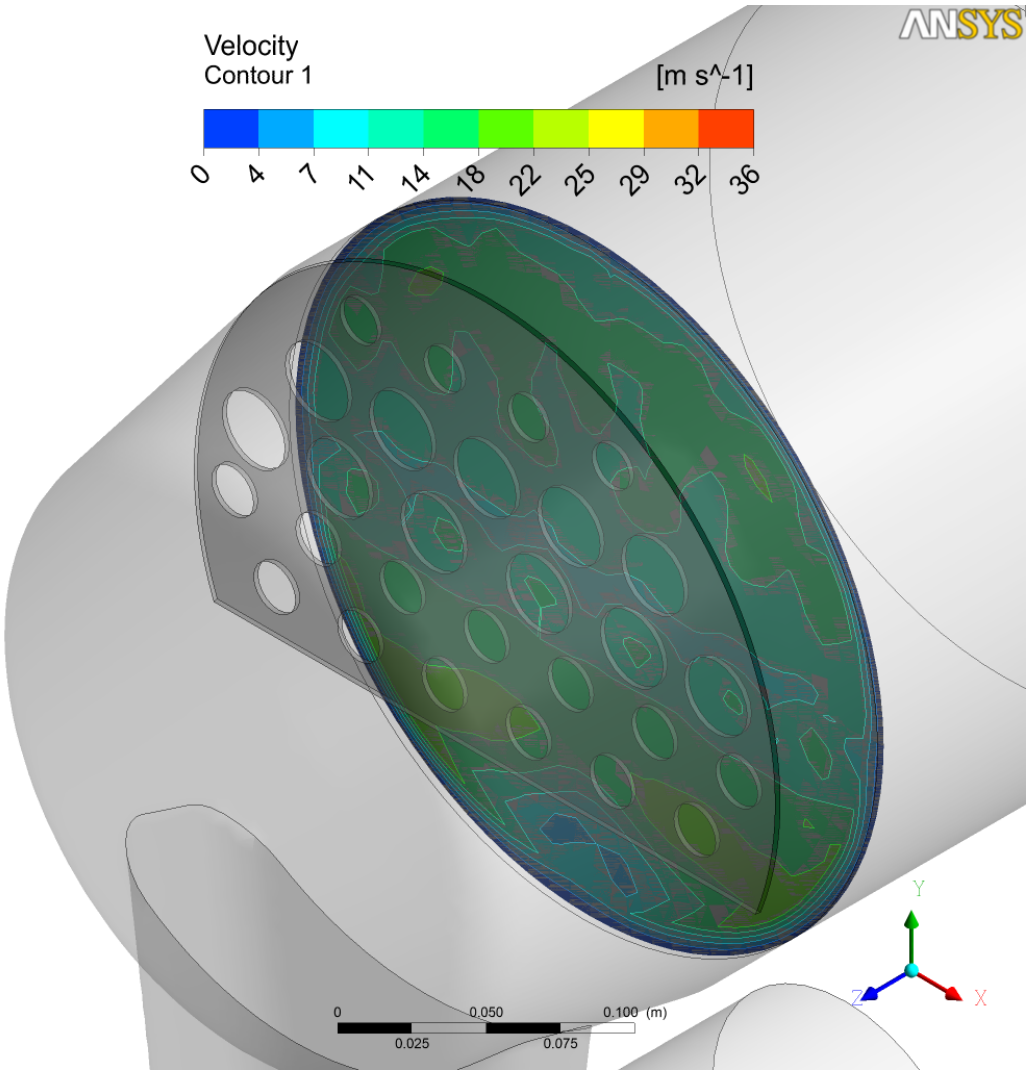

Figure 56: Case 3 velocity contour plot on a plane located at the outlet of the inlet tank model of the optimum design of the random walk Level-2 search algorithm.

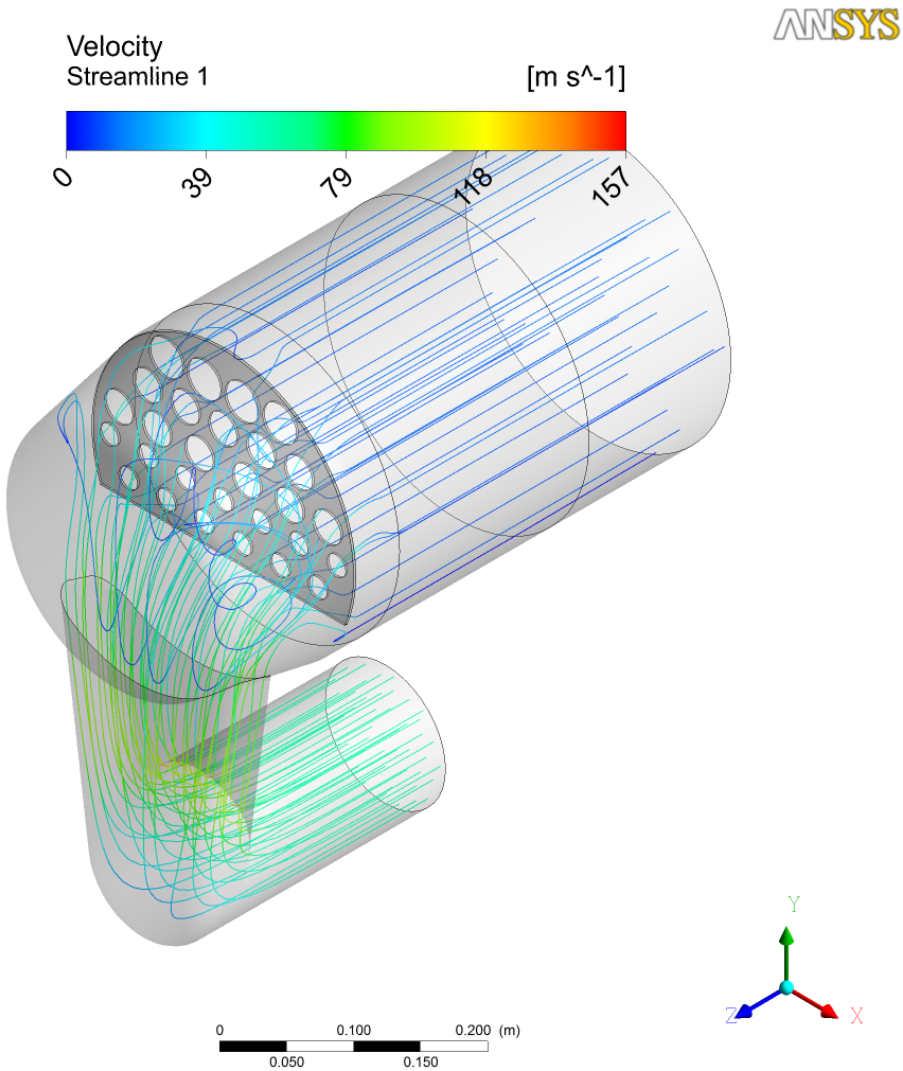

Figure 57: Case 3 streamlines in optimum design of the Min/Max Level-2 search algorithm.

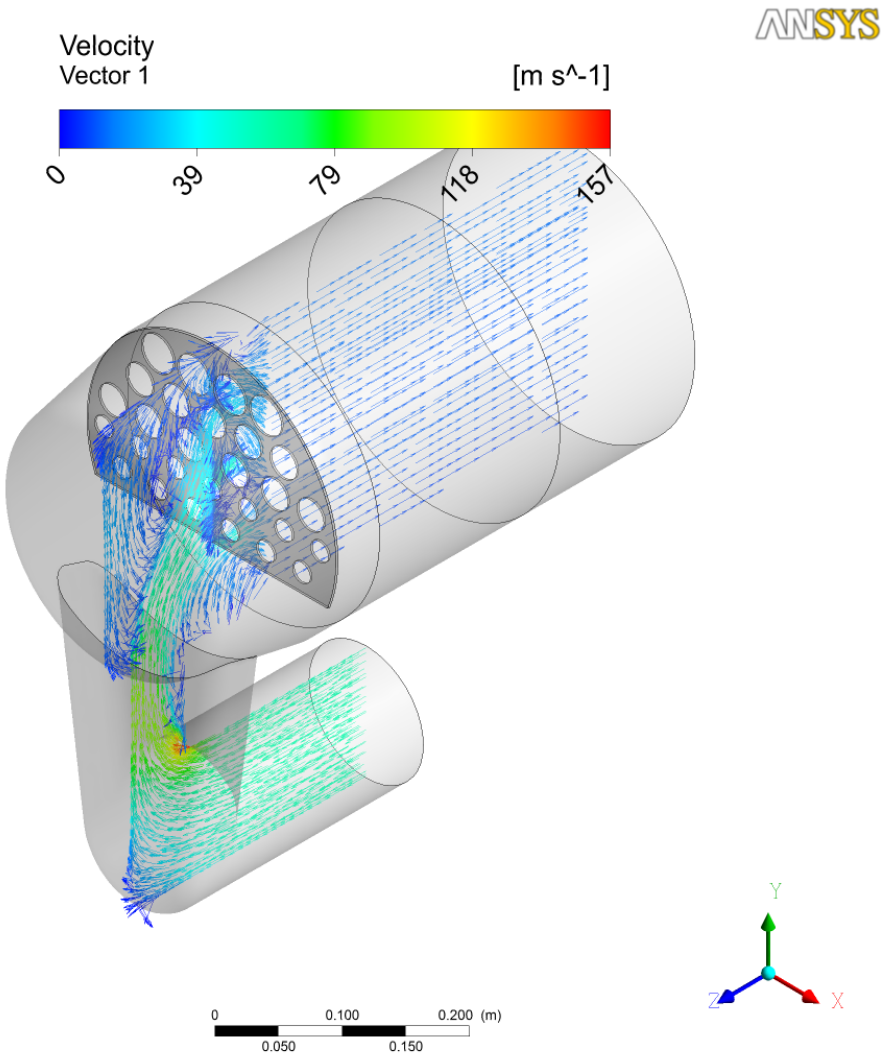

Figure 58: Case 3 velocity vector plot on a plane located through the center of the CFD model of the optimum design of the Min/Max Level-2 search algorithm.

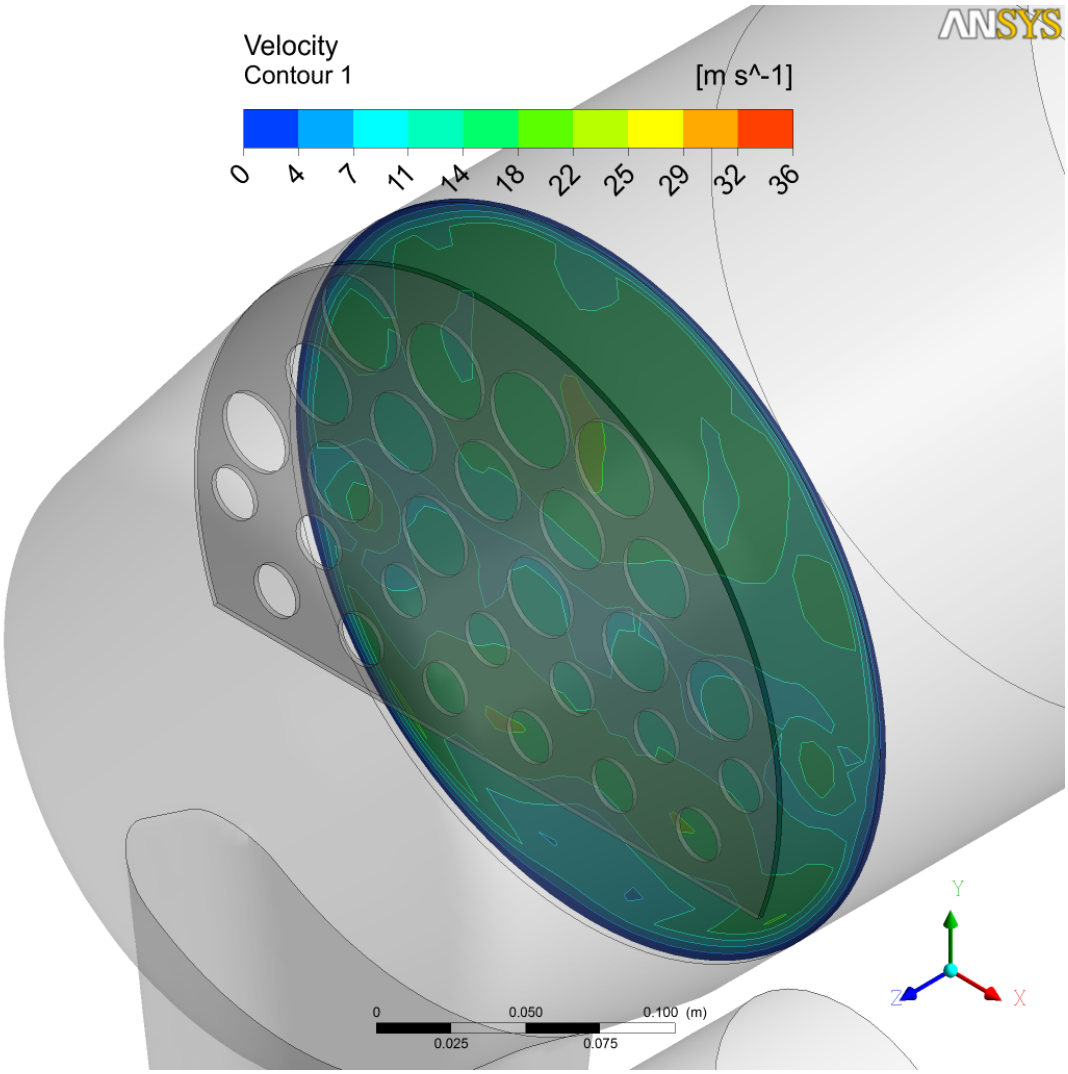

Figure 59: Case 3 velocity contour plot on a plane located at the outlet of the inlet tank model of the optimum design of the Min/Max Level-2 search algorithm.

The foregoing results show that the starting design for this case exhibited high mass flow uniformity at the exit of the inlet tank, but had a higher pressure drop than the optimum design. The data shows that the optimum design has a perforated plate height

of 0.190 m and has hole diameters that increase in diameter from the perforated plate edge to the outside wall of the inlet tank.

The optimum designs arrived at with the random walk and Min/Max Level-2 search algorithm have 12% less pressure drop and less than 0.5% reduction in uniformity. In this case, the engineer was focused on finding design solutions that had less than 2600 Pa pressure drop and a mass uniformity index greater than 0.85 while not changing the perforated plate height.

The generation of the response surface model required 17.93 hours of computer time, the generation of the Pareto-optimal design solution set required less than 2 minutes, and the average Level-2 optimization required 18 minutes.

In the second two example cases, the engineers are focused on the specific problems of minimizing pressure drop while maximizing induced flow, or achieving a mass flow uniformity index greater than a threshold value with minimum pressure drop. As the Level-2 optimization algorithm was run less emphasis was placed on the design variables needed to achieve the desired design solution performance, rather the design solution performance was chosen and the associated design variables were then considered.

In case one the engineer was focused on finding an optimum design of an air passage for a liquid to air heat exchanger that exhibited low air side pressure drop and high heat flux. As the Level-2 optimization algorithm was run component efficiency, manufacturing concerns, and system integration were all higher level information that was used to select the optimum designs. By using the method developed in this thesis,

any decision made to choose a design solution is assured to be an optimum design solution due to the use of the Pareto-optimal design solution set as the input to the Level-2 optimization algorithm.

Previous to the use of the method presented in this thesis the decisions made during the PDP have occurred in a haphazard manner in the design variable space rather than in both the design variable and objective space. Normally this leads to design solutions that are not optimum and excessive engineering decision time. As the three example cases, this is no longer the case when the method presented in this thesis is used.

CHAPTER 7 : CONCLUSIONS AND FUTURE WORK

This chapter summarizes the conclusions drawn from this work as well as suggested future work.

7.1 Conclusions

A simulation workflow that couples CFD with multi-objective, multi-level optimization has been developed which enables the integration of CFD models earlier in the PDP to facilitate engineering decision making early in the PDP. The simulation workflow has the features of:

1. Application to internal flow fluid thermal components characterized by incompressible, non-reacting, ideal gas flows.
2. Ability to make use of commercial CAD and CFD software
3. Multi-objective optimization to generate Pareto-optimal design solutions
4. User in the loop Level-2 optimization

The method presented in this thesis starts with definition of a design problem, the associated design variables, and the design solution objectives. Based on this information a parameterized CAD model of the fluid domain is generated. The CAD geometry is then passed to a CFD mesher where the mesh is generated. With the mesh generated the

CFD solver is setup to calculate the design solution objectives according to the physics of the design problem.

Depending on the solution time for the CFD model one of two approaches is taken. If the CFD model requires significant calculation time the first approach is taken; which makes use of a central composite DOE to sample the design variable space as input to a response surface model. The Level-1 multi-objective optimizer uses the NCGA multi-objective optimization algorithm coupled with the response surface model to calculate the Pareto-optimal design solution set. The second approach is to couple the multi-objective optimization algorithm directly to the CFD model. Both approaches lead to the Pareto-optimal design solution set.

Once the Pareto-optimal design solution set is generated the Level-2 optimization algorithm is run. This optimization algorithm can use a random walk search algorithm or a Min/Max search algorithm to search the Pareto-optimal design solution set. As the algorithm searches the Pareto-optimal design solution set, the engineer evaluates the fitness of each design based on higher level information. The Level-1 optimization uses commercial software with the appropriate custom plug-ins to allow the CAD and CFD software to share information. The Level-2 optimization algorithm is written in C++.

The method presented in this thesis was demonstrated on three example problems as summarized below.

1. Case 1: Determine the flat length and radii at the top of a cooling fin that maximizes heat flux and minimizes pressure drop.

2. Case 2: Determine the combination of nozzle diameter, immersion, and exhaust pipe diameter that embody a design solution of a jet pump that maximizes the induced flow and minimizes the jet pump pressure drop.
3. Case 3: Determine the combination of perforated plate height, perforated plate hole diameters, and inlet radius of an inlet tank that maximizes the mass flow uniformity index and minimizes pressure drop.

In Case 1 the Pareto-optimal design solution set contains 37 unique design solutions that minimize pressure drop and maximize heat flux. As the Level-2 optimization algorithm was executed with the higher level information of manufacturability and debris tolerance it is assured that the decisions that are made will produce a design that is optimum regarding pressure drop and heat flux because the decisions are being made on the Pareto-optimal design solution set from the Level-1 optimization. This case successfully identified heat exchanger fin designs that minimize pressure drop, maximize heat flux, is manufacturable, or is tolerant to debris.

In Case 2 the method presented in this thesis leads to a design solution of a jet pump that has 8% more secondary mass flow (induced flow) and a 16% reduction in pressure drop when compared to the starting design while considering the higher level information of the impact of the exhaust pipe diameter on aesthetics. The use of the method presented in this thesis provided a savings of nearly 6 weeks in design time when compared to the traditional mechanical design approach.

In Case 3 the design solution of an inlet tank that minimizes the pressure drop through the inlet tank while having a mass flow uniformity index above a threshold value

at the inlet tank outlet. The optimum design arrived at had 12% reduction in pressure drop with less than 0.5% reduction in the mass flow uniformity index. This design solution was arrived at while the engineer made decisions in the Level-2 optimization that avoided excessive manufacturing costs while being assured that the design chosen is optimum in regard to pressure drop and mass flow uniformity index.

Table 15 shows that as the CFD models contain more cells, the overall calculation time to arrive at the Pareto-optimal design solution set increases. The total calculation time without the use of the RSM is calculated for Case 2 and Case 3 as the total number of times the multi-objective optimizer requested a fitness evaluation multiplied by the time required for one CFD calculation to run. The total calculation time with the use of the RSM for Case 1 is calculated by multiplying the number of DOE runs by the calculation time for the one CFD calculation. All other time values are observed total calculation times. These results show that the method presented in this thesis has successfully made it possible for larger CFD models to be candidates for the design methodology presented earlier.

Table 15: Example case total calculation time to find Pareto-optimal designs.

Case	Number of Cells	Total Calculation Time Without The Use Of RSM	Total Calculation Time With The Use Of RSM
		Hours	Hours
Case 1: Fin	30000	16	0.31
Case 2: Jet Pump	55000	1034	7.75
Case 3: Inlet Tank	210000	4167	17.93

The three example cases show that this method has effectively assisted in determining an optimum design in the presence of higher level information. The simulation framework developed here facilitates engineering decision making by finding a Pareto-optimal design solution set first and then aiding the engineer in determining the optimum design based on higher level information.

The method presented in this thesis contributes the following to the state of the art:

- Use of response surface models to optimize on when needed to allow larger CFD models to be candidates for optimization.
- Develops a simulation workflow that is applicable to general purpose internal flow fluid thermal components.
    - Software components that share the appropriate information between a CAD system, CFD mesher, CFD solver and multi-objective optimizer.

    - Software components developed in Java scripting, Linux, and DOS scripting
- User in the loop optimization algorithm
    - Software developed in C++ using object oriented programming
        - Two search algorithms that search the Pareto-optimal design set.

7.2 Suggested Future Work

The design methodology developed in this thesis offers the following opportunities for future work:

- Develop a taxonomy of multi-objective algorithms that are best suited for various design problems.
- Extend this method to design systems and sub-systems of greater complexity like building cooling systems, power-train cooing systems among others.
- Development of more Level-2 search algorithms that reduce the time to arrive at an optimum design.
    - When this method is applied at a system or sub-system level with greater than 500 Pareto-optimal design solutions a search algorithm that reduces the Level-2 optimization time is needed.
- Increase computational efficiency by developing:
    - Parallel evaluation of the DOE runs.

- Making use of parallel multi-objective optimization algorithms in the Level-1 optimization.

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