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Orthogonal decomposition as a design tool: With application to a mixing impeller

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Orthogonal decomposition as a design tool: With application to a mixing impeller

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ABSTRACT

Digital manufacturing eliminates the expense and time required to develop custom products. By utilizing this technology, designers can quickly create a customized product specifically for their performance needs. But the timescale and expense from the engineering design workflows used to develop these customized products have not been adapted from the workflows used in mass production. In many cases these customized designs build upon already successful mass-produced products that were developed using conventional engineering design workflows. Many times as part of this conventional design process significant time is spent creating and validating high fidelity models that accurately predict the performance of the final design. These existing validated high fidelity models used for the mass-produced design can be reused for analysis and design of unknown products. This thesis explores the integration of reduced order modeling and detailed analysis into the engineering design workflow developing a customized design using digital manufacturing. Specifically, detailed analysis is coupled with proper orthogonal decomposition to enable the exploration of the design space while simultaneously shaping the model representing the design. This revised workflow is examined using the design of a laboratory scale overhead mixer impeller. The case study presented here is compared with the design of the Kar Dynamic Mixer impeller developed by The Dow Chemical Company. The result of which is a customized design for a refined set of operating conditions with improved performance.

CHAPTER 1

INTRODUCTION

In a world of complex products, processes, and systems effective engineering design is critical. Decisions made during the engineering design process have far reaching influence impacting quality and performance of the product and controlling 75% of the total product cost (Dieter and Schmidt 2013, 4). In the same way the decisions made during conceptual design similarly have significant impacts later on towards the finished product even though the majority of time spent in the design process is often dedicated toward these latter stages (Childs 2004, 6). Because of this, analysis has become an important tool in these stages that results in accurate simulations of the product, process, or system without ever leaving the computer. Some of these analysis tools are computer-aided design (CAD) and computer aided engineering (CAE). CAD eliminates the dependence on rough approximations and enables the development of complex three-dimensional geometries coupled with an ability to simulate design performance (Mitchell 1999). CAD allows for entire systems to be designed such as the complicated structures of modern airliners from simple parts such as a bolt to a complete assembly containing millions of parts (Dietrich, Stephens and Wald 2007). In addition to the design and assembly, computational tools analyze the system and its overall response. For example, finite element analysis (FEA) has the capabilities to simulate statics, dynamics, thermal responses, vibrations, and fluid mechanics; using FEA designers no longer rely on an idealized or experimental model when making critical design decisions but instead are using analysis to save time and improve the product (Dieter and Schmidt 2013, 276). These tools continue to improve as compute power becomes cheaper and more detailed

models can be considered thus resulting in more accurate simulations that are easily obtained (Rubbert 1990, Suh 1990, 16). In spite of this the role of detailed analysis tools, such as computational fluid dynamics within engineering design, has been limited to the final detailed analysis phase of the engineering design process.

The three phases of engineering design begin with the definition of the problem and its design space; this then leads to the generation of designs that meet these defined needs. Beyond these initial steps the considered designs are reduced from a collection of many designs to one detailed design through a series of more and more detailed analysis processes. Instead conceptual designs are quickly generated and coarsely eliminated based upon the problem definition and design space constraints. Once a handful of concepts are found the preliminary design phase further refines them until one chosen design is found. Rudimentary models are used to conduct this refinement such as those used to determine the weight, size, and function of the device. Finally detailed design implements detailed modeling and analyzes the results in high fidelity and time consuming simulations. The result of which determines whether the design is ready for production or requires further analysis or even a complete redesign.

To expand the role of detailed analysis in engineering design it must be extended to all three phases: conceptual, preliminary, and detailed (Ertas and Jones 1993, 3, Pahl et al. 2007, 130). For example, computational fluid dynamics is one of these powerful analysis tools used in the engineering design process. However, CFD requires significant time and compute power. As a result, the resources and time of the investigator are limited, leaving many variations within the geometries design envelope hidden, thus restricting the number of designs considered. A different approach is needed that reduces the amount of computation

time required for investigation without sacrificing the accuracy of the simulation. Constructing the computational models necessary for effective high fidelity models can take weeks or even months. Additionally, to achieve accuracy a collection of computational simulations is needed to support engineering design, further increasing the amount of time required to obtain results. Due to the significant amount of time detailed analysis requires, these types of detailed modeling tools are rarely used in the early stages of the design process. This is in contrast to the critical role the early stages of design play in the cost and performance of the final product.

In a 2006 report the National Science Foundation (NSF) identified the importance of simulation, finding that high fidelity tools are critical to engineering science because they allow the exploration of ideas that otherwise could not be developed without the use of simulation (National Science Foundation 2006). Creative engineering design commonly occurs during the conceptual and preliminary design phases where ideas are investigated and explored. High fidelity modeling provides an opportunity to improve the quality and innovation associated with designs generated at these stages. But the time scales between these two aspects of engineering design are so disparate that detailed analysis is not conducted in the current structure of engineering design workflow.

This thesis implements reduced order modeling using proper orthogonal decomposition of the results of computational fluid dynamic simulations. Orthogonal decomposition creates reduced order models from multiple sets of data (snapshots). In the case of high fidelity models, these snapshots are individual runs of the model exploring a specific set of independent variables. Developing a reduced order model of a complex flow from computational or experimental data is similar to the exploration of concepts and designs

during the conceptual and preliminary phases of engineering design. In both cases the goal is to understand the impacts of independent variables (design choices) and to explore the proposed design space. As the design space is explored and understood, some concepts and designs are chosen for closer examination and some are discarded. In this way the designers can use the most current results of the analysis while exploring the design space and while the analysts continue to run additional cases and improve the accuracy and applicability of the reduced order model as the design evolves. At the same time the model and the ROM can be refined as the design is refined. That is, the ROM for a design and the design can be developed and refined simultaneously as a part of the design exploration and refinement process.

To provide an easily understood design environment, the analysis and design results are integrated together into a visually based environment that can be used to explore various design options and provide the expected results in real time. This enables the design process to flow smoothly from the conceptual design exploration process, through the down select process, and to a detailed design using the same set of models and information within an interactive and collaborative design paradigm. In addition,

- By utilizing a continuously updated integrated computational model, the models and information developed as well as the design and decision making narrative are automatically preserved and available for future reference should the need arise.
- Decoupling the analysis and design process while ensuring that the same data is used brings high fidelity modeling into the design process during the conceptual design phase rather than as a validation tool much later in the detailed design process.
- Working within a graphically based integrated computational environment provides a

easily understood common workspace for analysts, designers, and users throughout the design process.

This thesis presents high fidelity modeling coupled with proper orthogonal decomposition integrated into engineering design workflow. Beginning in Chapter 2 discusses the current avenues of research in engineering design workflow and proper orthogonal decomposition. Following this, Chapter 3 presents a journal article that is being prepared for submittal that implements a case study contrasting the workflows, processes, and design outcomes of the two design processes, which are compared and discussed. Finally, in Chapter 4 conclusions are developed and future work is discussed.

CHAPTER 2

BACKGROUND

Detailed analysis tools such as computational fluid dynamics are powerful instruments within the engineering design process. The importance of these tools becomes magnified as system design becomes ever more complex. But due to the time required for detailed analysis tools to provide accurate results, they are often underutilized. Not only is significant compute power and time required to run these models, but also significant time is required by analysts to construct and validate these models. To overcome these challenges, many have simply used more and more compute power with diminishing returns. Additionally, when more compute power does become available stakeholders often choose to conduct a higher fidelity analysis that leads to slightly more accurate results but with a similar compute time. Some though have made attempts to overcome this issue and integrate modeling and analysis into the conceptual or preliminary phases of engineering design by reducing the amount of analysis time required. Examples of this include speeding up the reanalysis process (McCorkle, Bryden and Carmichael 2003), using simplified representations of the problem (Meng et al. 2013), reduced order models that address a single critical aspect of the design (Bourguet, Braza, and Dervieux 2011), or orthogonal decomposition to rebuild a complex aspect such as the flow field (Muld, Efraimsson, and Henningson 2012). Although faster solutions address many of these issues, fully utilizing faster more detailed models earlier in the design process requires that the modeling workflow and the design workflow be explicitly linked together.

2.1 Engineering Design Workflow

As briefly discussed in Chapter 1, the engineering design process can be divided into three main phases; conceptual, preliminary, and detailed design phases. Recently, Spitas (2011) conducted a review of industrial design workflows that are currently used throughout industry. The results found an evolution of the design process. Initially, in a designer's career their chosen workflow is shaped by their education. Then their workflows become tailored to fit their own experiences as they progress in their careers. Spitas also found that there were three different engineering design workflows currently used in industrial design: abstraction-to-detail, detail-to-detail, and detail-to-abstraction-to-detail. Abstraction-to-detail is often thought of as the engineering design process and is widely taught in engineering schools. Within this workflow designers and collaborators systematically work through each step moving from concept to production (Pahl and Beitz 1988). Initially, the problem and design space are defined and this then leads to the generation of concepts that fit within this rudimentary criteria. Concepts are either eliminated or refined based upon a set of models developed to meet the needs for the defined problem. Finally, one design remains that undergoes time-consuming detailed analysis such as CFD or FEA. The results of the analysis either meet the defined criteria and the design moves into production, or the design fails to meet these criteria, resulting in a redesign and returning the process to earlier design phases. The detail-to-detail design workflow focuses on the design of the next generation of previously designed products (Ottoson 1996, Ottoson 2004). Detail-to-detail design removes the initial steps of abstraction-to-detailed design workflow since incremental improvements are made to an already produced product. The detail-to-abstraction-to-detail design process is similar to the abstraction-to-detail design process except that a knowledge database is

constructed of current products within the appropriate design field. The initial steps in detail-to-abstraction-to-detail focus on exploring the current solutions and improving upon manufactured designs (Braha and Maimon 1999, Maimon and Braha 1999). Spitas identified these three design workflows noting that they differed in their initial phases but all share a common linear progression toward one final design in which detailed analysis plays a critical role. But the role of detailed analysis in engineering design is still limited to the final few designs (or perhaps only the final design) due to the time needed for detail models.

Recent research has identified two critical areas for which these tools affect engineering design. The first group focuses on developing software that better manages and organizes the knowledge generated in the design process for current and future work. The second area of research works to develop tools that reduce the computation time within certain phases of the design process. Several researchers have recently developed software tools for the management and organization of the information produced during the design process. Often a knowledge management system is the first tool looked at for integration into the design process. Capturing information associated with the design process as it progresses enables designers, engineers, and other collaborators to view the same information simultaneously. Additionally, due to the complexity of products developed using engineering design, these stakeholders are often from other disciplines and locations. Li and Liu (2012) discussed a web-based knowledge management system to overcome this disparity in engineering design knowledge and physical distance between actors using multidisciplinary optimization. Many of these knowledge management tools require significant amounts of user input to accurately capture the process as it progresses. Recently, though the automation of design characteristics and information has been implemented by recognizing part shapes

contained within a design and the associate corresponding information for the part (Catalano et al. 2009, Yang et al. 2012). Roldán, Gonnet, and Leone (2010) developed a software environment to capture the design process but then enabled users to apply the same workflow to a design process for a similar part or product in the future.

In the same way many researchers have sought to integrate software tools that support computational modeling into various parts of the design workflow. Some have focused on discrete sections of the design process such as Nagel et al. (2011) who integrated functional and process modeling during the conceptual design phase for two types of intelligent ground vehicle robots, one that disposed of explosive devices and the other that autonomously moved through challenging terrains. This integration of functional and process modeling then determined the workflow for the remainder of the design process of two similar technologies with significantly different design goals. Others have chosen to integrate software tools for engineering design into a web-based interface resulting in one unified piece of software accessible usable by all collaborators and having the ability to easily implement high performance computing without having to have onsite access to the compute power (Yu et al. 2010, Alexopoulus et al. 2011, Weng 2011, Lwin et al. 2012, McIntosh et al. 2012, Ari and Muhtaroglu 2013, Wang and Takahasi 2012, Valilai and Houshmand 2013). A collection of tools has been developed within these unified systems or as stand-alone pieces of software that generate and swiftly analyze designs during the conceptual design phase. The capabilities of these tools have included algorithms that make design decisions based upon previous experiences (Kurtoglu, Swanter and Campbell 2010, Chen, Liu and Xie 2012), tools that complete rough sketches for different types of clothing (Ma et al. 2011), automatic mesh generation for the design of concepts (Iványi 2013), graphs that quickly present

pertinent information based upon user generated concepts (Pyl, Sitters, and De Wilde 2013), and structural analysis of generated concepts (Svoboda et al. 2013). Tools have also been developed for conceptual design of aircraft in software environments that incorporate the analysis of geometry, models, and some detailed models (Cavagna, Ricci, and Travaglini 2011, Rizzi 2011). Richardson et al. (2011) implemented one of these software environments in the design of a small jet powered aircraft and found it to be useful when developing novel geometries. Other solutions have included quickly analyzing designs for characteristics such as lifetime (Bohm et al. 2010), reliability (Liu, Huang, and Ling 2013), complexity (Caprace and Rigo 2012), and cost, (Cheng, Tsai, and Sudjono 2010, Lin, Lee and Bohez 2012, Mellichamp 2013).

Several researchers have examined how to analyze more information during the preliminary design phase while performing faster analysis to support a quicker down select process. Thompson (2012) integrated CFD into the preliminary design phase by developing a CFD solver that used a velocity transportation boundary condition as opposed to the common mesh motion solvers. A distributed computing environment was then used in concert with this modified solver that then resulted in time-savings applicable to preliminary design. Another approach that has been examined is initiating automatic volume and surface meshing during the preliminary phase that then eliminates time spent meshing in detailed design (Tomac and Eller 2011). Others have added intelligence to detailed analysis when used in optimization by automatically eliminating unsuccessful designs (Tenne 2012). Heuristics have been applied to the design process by searching for an improved design outcome coupled with a reduced amount of time in the model development and validation phase prior to preliminary design (Marti and González-Vidosa 2010, Carbonell, González-Vidosa, and

Yepes 2011). Azamatov et al. (2011) developed a design tool that quickly generated aircraft shapes pulling from a pool of common characteristics based upon the designer's specifications. The software then could analyze the different components of the aircraft or the system as a whole for parameters such as weight, size, and performance. In many ways these two research areas of knowledge management and software to reduce computation time during the design process are interrelated. As high fidelity modeling tools are adapted to address conceptual and preliminary design, analysts will be able to create large amounts of data that may or may not provide meaningful guidance. Each of these tools addressed a goal to organize the complex flow of information during the engineering design process but did not actively enable collaborators to develop improved design decisions.

2.2 Proper Orthogonal Decomposition

Reduced order models (ROMs) have been used to reduce the time needed to compute a flow field by one to two orders of magnitude over computational fluid dynamics (Alonso, Velaquez and Vega 2009, Barone et al. 2009, Bache et al. 2012, Walton, Hassan, and Morgan 2013). There are various types of reduced order models, these include the reduced basis method (Knezevic, Ngoc-Cuong, and Patera 2011), balanced truncation (Singler and Batten 2009, Ma, Ahuja, and Rowley 2011), and goal-oriented (Carlberg and Farhat 2011). While each of these has advantages and disadvantages, proper orthogonal decomposition has been found to be particularly effective for the reproduction of detailed flow fields. Because of this, it has been used in a number of applications related to design. One example utilizes a reduced order model to predict how the deformations of an airfoil affect the resultant flow over the changing airfoil design (Bourguet, Braza, and Dervieux 2011). ROMs demonstrated an important use where the results of small design changes needed to quickly be recomputed.

Azam and Mariani (2013) used proper orthogonal decomposition to predict the structural response for building different designs under varied seismic conditions. Ensuring that already constructed building would stand up to some of the worst-case scenarios in recorded history and additionally be used as a design tool for future buildings constructed in earthquake prone regions. Proper orthogonal decomposition was used in the design of an automotive cold air intake port thus reducing the number of considered variables that were critical to the ports performance (Xiao et al. 2012). Bizon and Continillo (2012) used reduced order modeling with a penalty function in the comparison of two designs of complex chemical reactors. The penalty function could increase the accuracy of the ROM but also added compute time to the overall simulation. For example it has been used to reconstruct and analyze bat wing kinematics from flight data, simplifying and enabling the visual exploration of bat wing design and motion (Pivkin, Swartz, and Laidlaw 2006). It has also been used to studying complex flow fields such as flame shedding for various geometries (Kostka et al. 2012). By using proper orthogonal decomposition, the critical parameters affecting performance could quickly be sorted from an abundance of data. In many fluid or thermal system designs a high fidelity model of a flow field will be developed during the detailed modeling process. By moving the development of the high fidelity model into the conceptual and preliminary design phases, the model can provide snapshots of the design space thus enabling a better understanding of the design options. Using the design of an impeller, this thesis examines the integration of orthogonal decomposition in the design workflow.

CHAPTER 3

ORTHOGONAL DECOMPOSITION AS A DESIGN TOOL: WITH APPLICATION TO A MIXING IMPELLER

Draft of paper to be submitted to Advances in Engineering Software

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Abstract

Digital manufacturing is a disruptive technology that enables customized products to be made quickly at little to no cost. Many times these customized products are developed for a refined set of operating conditions within the design space that result in improved performance over a mass produced product. In spite of the advantages of customized products, engineering design workflows have not yet been adapted to take advantage of this manufacturing technology. Rather, engineering design workflows are oriented towards mass production where one design is effective for a wide range of operating conditions. Thus the disparity in scale of cost and time required to design and manufacture one customized design may eliminate the value that can be gained from improvements in product performance. A new design workflow is presented in this research that overcomes this and enables a level of customization through the coupling of reduced order modeling using proper orthogonal decomposition and digital manufacturing. Reduced order modeling allows designers and engineers to quickly and accurately explore the design space using a collection of high

fidelity models. A case study is then presented that demonstrates the use of reduced order modeling to predict the flow fields that result from complex geometry changes. Finally, through the exploration of the case study design space a new customized design is identified for a refined set of operating parameters that results in an improvement in performance.

Keywords

Engineering design, reduced order model, proper orthogonal decomposition, mixing impeller, digital manufacturing

3.1 Introduction

Digital manufacturing is enabling customized designs to be manufactured at little to no cost in a rapid time frame. This disruptive technology has attracted significant attention and has been referred to as “the new industrial revolution” (Berman 2012). However, much of the power of digital manufacturing has not yet been realized because the engineering design workflows utilized to develop these customized products have not been adapted from the development of mass produced products. The high fidelity modeling and analysis techniques used in the engineering design process of mass produced products focus on developing the most effective design that covers the largest range of operating parameters, thus justifying these development costs for the design. In contrast the design process for a customized product can be tuned to a particular solution and need, but these one-off designs do not see the reduction in time and cost necessary to be feasibly developed. Today, the engineering design process is fully re-implemented for this customized design with the same time and expense creating and validating high fidelity models. Because of this, the design

space cannot be fully explored to identify designs with more effective performance for a subset of operating conditions. Our approach to reducing the design time for a uniform product is to use an established knowledge base from the high fidelity analysis of a mass-produced product.

High fidelity computational modeling is increasingly being used in engineering design. Tools such as computational fluid dynamics (CFD) and molecular dynamics can provide significant insight into the critical details of an engineered product, process, or system. Noting the power of simulation, a panel brought together by the NSF stated that high fidelity tools are critical to engineering science because they allow the exploration of ideas that otherwise could not be developed without the use of simulation (National Science Foundation 2006). However, the process of obtaining these insights is time consuming. Building, validating and verifying detailed computational models can take weeks and even months. Following this, the multiple runs needed to support engineering design are equally time consuming. As a result, modeling tools often have a limited role in engineering design.

The engineering design process can be thought of as consisting of three phases: conceptual design, preliminary design, and detailed design (Ertas and Jones 1993, 3, Pahl et al. 2007, 130). During conceptual design engineers explore the design space through the generation of concepts that then are filtered using the constraints defined for the problem. Following this, preliminary design further refines these concepts to one design. During the detailed design phase the chosen design is optimized and finalized. High fidelity modeling offers the power to improve and support creative engineering design in the exploration of ideas, which occurs during the conceptual design and preliminary design phases. But because of the time and expense required to develop, execute, and process these high fidelity models,

they are typically used primarily during detailed design.

This paper examines the use of proper orthogonal decomposition as a mechanism to bring detailed computational modeling into the workflow of the conceptual and preliminary phases of engineering design. Efficiently and effectively exploring the design space for improved performance from a customized design. Proper orthogonal decomposition (POD) has been used to create reduced order models (ROMs) that can rapidly reconstruct complex flow fields in time scales similar to digital manufacturing. For example, it has been used to reconstruct and analyze bat wing kinematics from flight data, simplifying and enabling the visual exploration of bat wing design and motion (Pivkin, Swartz, and Laidlaw 2006). It has also been used to study complex flow fields such as flame shedding for various geometries (Kostka et al. 2012). By using proper orthogonal decomposition, the critical parameters affecting performance can quickly be sorted from an abundance of data. POD creates ROMs from multiple sets of data (snapshots). In the case of high fidelity models these snapshots are individual runs of the model exploring a specific set of independent variables. Developing a reduced order model of a complex flow from computational or experimental data is similar to the exploration of concepts and designs during the conceptual and preliminary phases of engineering design. In both cases the goal is to understand the impacts of independent variables (design choices) and to explore the proposed design space. As the design space is explored and understood, some concepts and designs are chosen for closer examination and some are discarded. In many fluid or thermal system designs a high fidelity model of a flow field will be developed during the detailed modeling process. By moving that development of the high fidelity model into the conceptual and preliminary design phases, the model can provide snapshots of the design space thus enabling a better understanding of the design

options. At the same time the model and the ROM can be refined as the design is refined. That is, the ROM for a design and the design can be developed and refined simultaneously as a part of the design exploration and refinement process.

This paper first discusses the integration of proper orthogonal decomposition and high fidelity modeling into the design workflow developed to produce custom designs utilizing digital manufacturing. Following this, the proposed workflow is applied to the design of a mixing blade for lab-scale systems where rapid mixing is critical but difficult due to the inability to generate turbulence in small-scale systems. Finally, the impeller design space is explored to identify customized geometries shown to have improved performance characteristics for a refined set of mixing conditions, and then manufacturing the chosen design is manufactured.

3.2 Background

As noted earlier digital manufacturing has significant potential to improve the quality and reduce the cost of developing customized designs. However, much of this potential is not being realized because using traditional engineering design workflows, digital manufacturing cannot overcome the economies of scale from mass production. Within the engineering design process used for these mass-produced designs, significant time and expense are spent developing high fidelity computational models. But for the development of customized products, formulating a detailed model that can be used to explore the design is costly and impractical for a single case. However, in the case where the development of a customized product is an evolution of a successful design for which high fidelity models of the design have already been created and validated, these models can be used to develop customized

products. Additionally, in cases where a family of customized products is developed, a model covering the range of anticipated needs can be developed and validated for further customization of designs. However, in both cases the time to compute these models even after they have been built is prohibitive for use early in the design process.

However, shifting where and when high fidelity modeling is used in the design process could have far reaching implications particular in customized designs. Several approaches have been developed to bring significant reductions in the time needed for analysis to examine new design options. These include speeding the reanalysis process (McCorkle, Bryden and Carmichael 2003), using simplified representations of the problem (Meng et al. 2013), reduced order models that address a single critical aspect of the design (Bourguet, Braza, and Dervieux 2011), or orthogonal decomposition to rebuild a complex aspect such as the flow field (Muld, Efraimsson, and Henningson 2012). Although faster solutions address many of the issues, fully utilizing faster and more detailed models earlier in the design process requires that the modeling workflow and the design workflow be explicitly linked together.

3.2.1 Digital Manufacturing

Digital manufacturing has seen an increase in popularity due the reduction in machine costs, the expansion of manufactured materials, and the quality of produced designs. The term digital manufacturing is often used interchangeably with additive manufacturing, 3D printing and rapid prototyping. Adding to this confusion, there are many different types of digital manufacturing: fused deposition modeling, electron beam, metal laser sintering, selective laser melting, stereolithography, laminated object and digital light processing

(Gibson, Rosen, and Stucker 2010). Additionally, these different technologies are also developed for using certain materials such as thermoplastics, rubber, metal alloys, and photopolymers. Digital manufacturing was initially developed to reduce the time spent manufacturing prototypes during the preliminary phases of design (Horn and Harrysson 2012). But as the machine's quality improved the products were no longer limited to rough prototypes but now finished products. One area that has seen rapid expansion in the use of digital manufacturing has been the medical community producing customized devices such as dental implants (Khalyfa et al. 2007), orthopedic limbs (Melican et al. 2000) and hearing aids (Gibson, Rosen, and Stucker 2010) that fit each patients physiology. Furthermore digital manufacturing has been used to produce biological products such as ears (Liu et al. 2010), skin (Melchels et al. 2012), or organs (Mironov 2003). The need for customized products for individual users' needs is well established from research and advances in the medical community. But while the desires for customized products is well established, the workflows used to develop them do not translate effectively to other areas due to the time and expense spent developing these designs for specific conditions.

3.2.2 Engineering Design Workflow

As noted earlier, the engineering design workflow is often divided into the conceptual, preliminary, and detailed design phases. Within the framework of these phases, a number of design workflows have been suggested. However, a recent review of industrial design workflows has suggested that only three types of design workflow are routinely utilized in industry (Spitas 2011). These are abstraction-to-detail, detail-to-detail, and detail-to-abstraction-to-detail. Abstraction-to-detail is the systematic design process generally

taught in engineering schools. Because of this, it is often thought of as the engineering design process. As shown in Fig. 3.1, designers and collaborators systematically work through each step moving from concept to detail. Initially the problem and design space are defined that then lead to the generation of concepts that fit within this coarse criteria. Concepts are either eliminated or refined based upon a set of models developed to meet the needs for the defined problem. Finally, a sole design remains that undergoes time consuming detailed analysis such as CFD or FEA. The results of such analysis either meet the defined criteria and the design moves into production or if the design does not meet these criteria, a redesign occurs returning the process to earlier design phases. The detail-to-detail design work process focuses on the design of the next generation of previously designed products (Ottoson 1996, Ottoson 2004). As shown in Fig. 3.2, detail-to-detail design removes the initial steps of abstraction-to-detail design workflow since incremental improvements are made to an already produced product. A new problem definition and model development validation are superfluous since those same steps were already undertaken during the abstraction-to- detail design process of the currently produced product. The detail-to-abstraction-to-detail design process is similar to the abstraction-to-detail design process except that a knowledge database is constructed of current products within the appropriate design field. In all three types of design workflows management of the design process, communication of the details between disparate members of the design group, and remembering critical details as the design evolves are essential parts of the design workflow.

Fig. 3.1. Abstraction-to-Detail Design Workflow (Pahl and Beitz 1988)

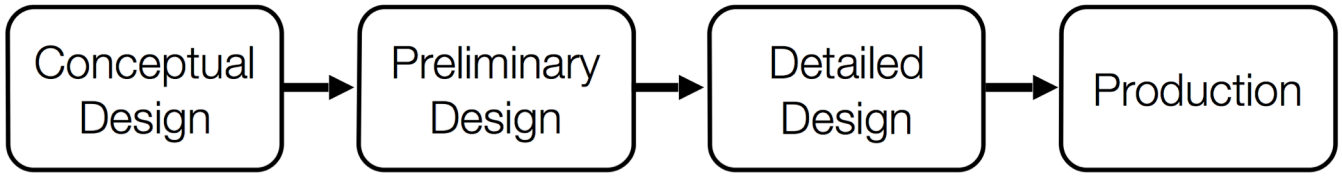

Fig. 3.2. Detail-to-Detail Design Workflow (Ottoson 1996)

Two areas of particular interest within engineering design that impact workflow are (1) developing tools that address the management, organization, communication, and remembrance of information during the design process; and (2) developing tools that reduce the computational time while increasing the range of options explored during the design process. In many ways these two issues are interrelated. As high fidelity modeling tools are adapted to address conceptual and preliminary design, analysts will be able to create large amounts of data that may or may not provide meaningful guidance. Several researchers have recently developed software tools for the management and organization of the information produced during the design process. These knowledge management systems try to capture information as the design progresses and enable designers, engineers, and other collaborators to view the same information. For example, web-based knowledge management systems have been proposed as a means to overcome the disparity in engineering design knowledge due to physical distance and differing skills and roles between actors while using multidisciplinary optimization (Li and Liu 2012). Automation of the identification of design characteristics and information has been implemented by recognizing part shapes contained within a design and associating the corresponding design information for the part (Catalano et al. 2009, Yang et al. 2012). A software environment has been developed that captures the workflow of the current design and then enables users to apply the same workflow to the design of a similar part or product in the future (Roldán, Gonnet, and Leone 2010). Each of these tools address the goal to organize the complex flow of information during the engineering design process but did not actively enable collaborators to develop improved design decisions.

In the same way many researchers have sought to integrate software tools that support

computational modeling into various parts of the design workflow. Nagel et al. (2011) integrated functional and process modeling during the conceptual design phase for two types of intelligent ground vehicle robots, one that disposed of explosive devices and the other that autonomously moved through challenging terrains. This integration of functional and process modeling then determined the workflow for the remainder of the design process of two similar technologies with significantly different design goals. Many have chosen to integrate software tools for engineering design into a web-based interface resulting in one unified piece of software accessible and usable by all collaborators and having the ability to easily implement high performance computing without having to have onsite access to the compute power (Yu et al. 2010, Alexopoulus et al. 2011, Weng 2011, Lwin et al. 2012, McIntosh et al. 2012, Ari and Muhtaroglu 2013, Valilai and Houshmand 2013). A collection of tools has been developed within these unified systems or as stand-alone pieces of software that generate and swiftly analyze designs during the conceptual design phase. The capabilities of these tools have included algorithms that make design decisions based upon past experiences (Kurtoglu, Swanter and Campbell 2010, Chen, Liu and Xie 2012), tools that complete rough sketches for different types of clothing (Ma et al. 2011), automatic mesh generation for the design of concepts (Iványi 2013), graphs that quickly present pertinent information based upon user generated concepts (Pyl, Sitters, and De Wilde 2013), and structural analysis of generated concepts (Svoboda et al. 2013). This has included quickly analyzing designs for characteristics such as lifetime (Anand and Wani 2010, Bohm et al. 2010, Böckmann and Schmit 2012), performance (Leutenegger, Jabas, and Siegwart 2011, Ferreira and Gil 2012), reliability (Cui and Wu 2011, Liu, Huang, and Ling 2011), complexity (Caprace and Rigo 2012), and cost (Cheng, Tsai, and Sudjono 2010, Lin, Lee and Bohez 2012).

Several researchers have examined how to analyze more information during the preliminary design phase while performing faster analysis to support a quicker down select process. Thompson (2012) integrated CFD into preliminary design by developing a CFD solver that used a velocity transportation boundary condition as opposed to the common mesh motion solvers. A distributed computing environment was then used in concert with this modified solver that resulted in timesaving applicable to preliminary design. Another approach that has been examined is initiating automatic volume and surface meshing during the preliminary phase that then eliminates time spent meshing in detailed design (Tomac and Eller 2011). Others have added intelligence to detailed analysis when used in optimization by automatically eliminating unsuccessful designs (Tenne 2012). Heuristics have been applied to the design process by searching for an improved design outcome coupled with a reduced amount of time in the model development and validation phase prior to preliminary design (Marti and González-Vidosa 2010, Carbonell, González-Vidosa, Yepes 2011). Azamatov et al. (2011) developed a design tool that quickly generated aircraft shapes pulling from a pool of common characteristics based upon the designer's specifications. The software then could analyze the different components of the aircraft or the system as a whole for parameters such as weight, size, and performance.

In this article we propose integrating detailed analysis into the abstraction to design workflow and are working to bring computational tools in earlier; this may also help overcome the objections of moving to an abstraction-to-detail workflow by reducing the time and cost and improving the added value.

3.2.3 Proper Orthogonal Decomposition

Reduced order models are commonly used to reduce the compute and wall clock time needed to find a new result rather perform another set of detailed computations (Fang et al. 2009). For example, ROMs have been used to reduce the time needed to compute a flow field by one to two orders of magnitude over computational fluid dynamics (Alonso, Velaquez and Vega 2009, Barone et al. 2009, Bache et al. 2012, Walton, Hassan, and Morgan 2013). There are various types of reduced order models; these include the reduced basis method (Knezevic and Patera 2011), balanced truncation method (Ma, Ahuja, and Rowley 2011), boundary element method (Noorian, Firouz-Abadi, and Haddadpour 2012) and goal-oriented method (Carlberg and Farhat 2011). While each of these has advantages and disadvantages, proper orthogonal decomposition has been found to be particularly effective at the reproduction of detailed flow fields. Because of this, it has been used in a number of applications related to design. One example utilizes a reduced order models to predict how the deformations of an airfoil affect the resultant flow over the changing airfoil design (Bourguet, Braza, and Dervieux 2011). Reduced order models demonstrated an important use where the results of small design changes needed to quickly be recomputed. Azam and Mariani (2013) used proper orthogonal decomposition to predict the structural response for building of different designs under varied seismic conditions, thus ensuring that already constructed building would stand up to some of the worst-case scenarios in recorded history and additionally be used as a design tool for future buildings constructed in earthquake prone regions. The technique has also been used in modeling the thermal properties to improve the design of data centers (Samadiana and Joshi 2010) and lithium ion batteries (Suhr and Rubeša 2013). Additionally, Mifsud, Shaw, and MacManus (2010) used POD for the design of high-speed

weapons systems for air combat noting that POD is a reliable tool but does depend on the quality of simulations used to construct it. Bizon and Continillo (2012) used reduced order modeling with a penalty function in the comparison of two designs of complex chemical reactors. The penalty function could increase the accuracy of the ROM but also added compute time to the overall simulation.

This section provides a brief overview of proper orthogonal decomposition; for a more detailed discussion the reader is referred to (Kirby 2001). Proper orthogonal decomposition is used to find a set of optimal truncated orthogonal basis functions u_i from a training set of snapshot solutions. The snapshot solutions x_{sol} are typically obtained from numerical simulations spanning the design space of interest. To find the optimal set of truncated basis functions needed for the reduced-order model, first the set of snapshot solutions, M in number, are centered by computing and subtracting the mean of the data set from each snapshot. These mean-subtracted snapshots are concatenated into a single ensemble matrix $x_{N,M}$ where N is the size of each snapshot vector. The basis functions are computed from the covariance of this ensemble matrix using the SVD technique. Any solution within this design space can then be computed using the basis functions as show in Eq. 1, where D is the dimension of the truncated vector space.

$$x_{sol} = \sum_{i=1}^{D} a_i u^i \tag{1}$$

Where the a_i are the coefficients that are used to compute the orthogonal decomposition approximation for a given set of basis functions, which are computed by projecting the basis functions onto the original ensemble matrix.

Once the basis functions and coefficients are known, any design with the design space can be evaluated. For evaluating designs already in the initial design space, the coefficients

are used directly. However, to evaluate designs not in the design space, a linear interpolation of coefficients is performed as shown in Eq. 2.

$$a^* = a\big|_{q_k} + (a\big|_{q_{k+1}} - a\big|_{q_k})\frac{(q^* - q_k)}{(q_{k+1} - q_k)} \tag{2}$$

Where q^* satisfying $q_k < q^* < q_{k+1}$ is the design parameter that is being evaluated and a^* is the set of new coefficients. A cosine similarity index is used to find the design vectors q_k and q_{k+1} that are closest to the parameter q^*.

As a design is developed using abstraction-to-detail design workflow, more and more analysis is conducted as the design is refined toward a finished product. That is, as a design moves from the conceptual phase to the preliminary phase and finally to the detailed phase with this progression, the number of different analysis methods increases along with the level of refinement for each method. Proper orthogonal decomposition works in a similar way for creating reduced order models; as more snapshots are added to the ROM the higher the accuracy the ROM outputs (Brenner et al. 2012). The snapshots that are used to construct the ROM are taken from the analysis methods used during the design process. The snapshots are defined by a set of parameters that describe the flow field from the simulation. The ROM then uses the parameters to define the design space such that when queried it understands what flow fields result from specific operating conditions. Initially, only a small amount of information is available about the design space from the methods of analysis used during the early design phases, which leads to a coarse definition of the design space. But as more and more analysis is conducted on the design, the results from the reduced order model drastically increase with accuracy.

3.3 Proposed Design Workflow

This work builds upon abstraction-to-detail design workflow with the inclusion of reduced order models throughout the design process. With the addition of this tool a greater expanse of designs can be considered and accurate design decisions can be made. The proposed workflow can be seen in Fig. 3.3. The design process begins similarly to abstraction-to-detail design workflow with a definition of the problem at hand and a coarse understanding of the design space. After these two steps though, the design workflow separates into two simultaneous workflows, one focusing on the development of models used for analysis and another focusing on the designs as they progress to one final design. A small series of snapshots are taken from a limited run of analysis of designs generated in the conceptual phase. The results from this collection of snapshots are inaccurate for detailed design selection but are critical in providing the ROM with a basis of the extremes for the design case. This information for the boundaries of the design space then informs the refinement of the design on the path toward detailed design. More snapshots are then generated as more cases are considered, thus improving the accuracy of the reduced order model. At this point the ROM has obtained enough information about the design space such that accurate predictions can begin to be made. The results from the use of the ROM in this phase can fully inform the designers for the final characteristics of the design such as geometry and operational parameters such as rotational velocity or viscosity of the working fluid. From this information designers can choose a final design based on a set of already known characteristics, which the ROM has informed them of. Often in abstraction-to-detail

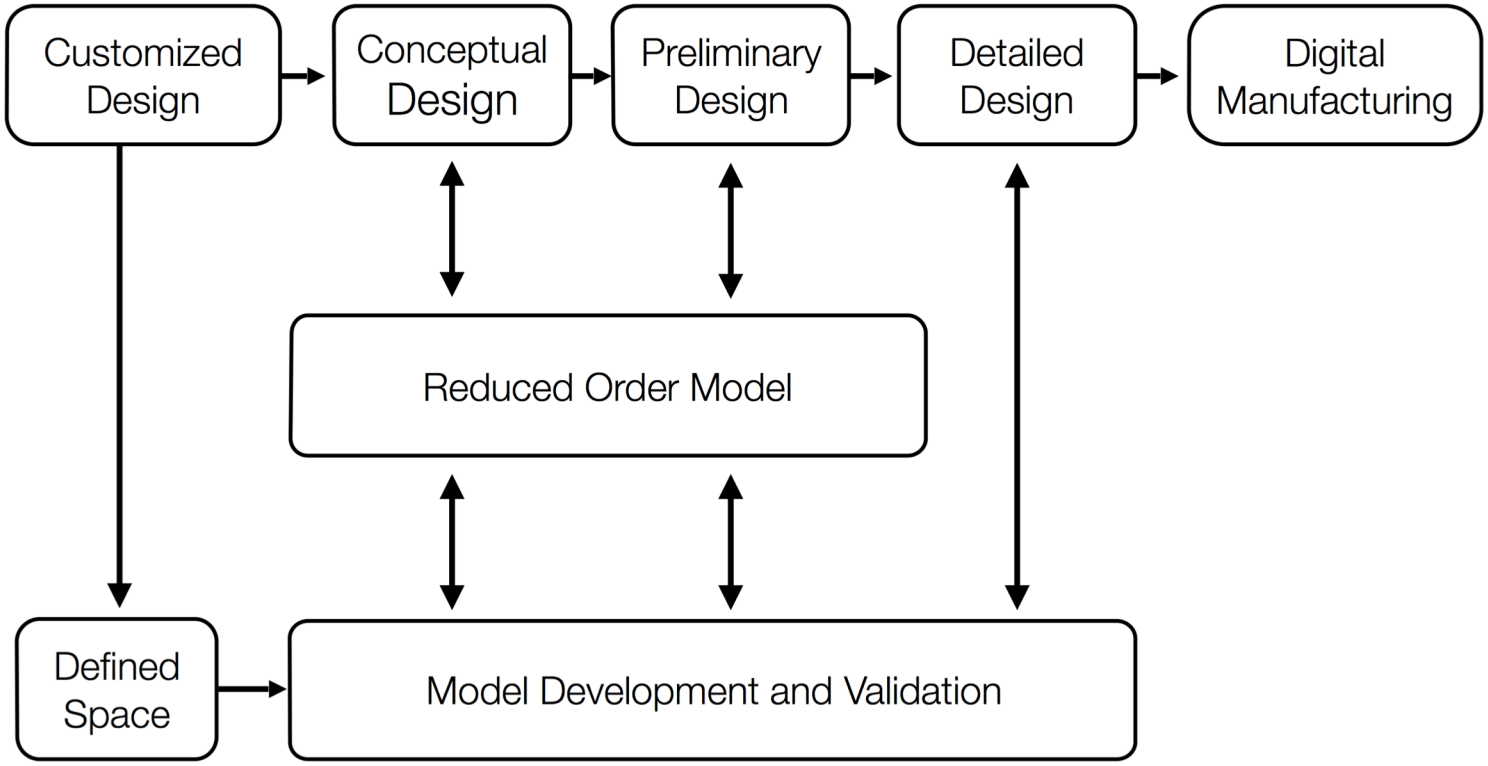

Fig. 3.3. Proposed Engineering Design Workflow Using Orthogonal Decomposition

design workflow, redesigns occur that require collaborators to return to the conceptual or preliminary design phases thus restarting a majority of the process again. The inclusion of ROMs allows these stakeholders to make far-reaching design changes and know the results of these changes almost instantly.

3.4 Design Application

To implement this proposed design workflow, a case study was needed that could be adaptable for this research. The case study needed to have an already developed and manufactured design using conventional engineering design workflows. The existing design used in this research is the Kar Dynamic Mixer (KDM) impeller, Fig. 3.4, developed by The Dow Chemical Company (Kar, Somasi, and Cope 2011). The design uses novel mixing blade placements and impeller sizes to reduce the amount of time needed to mix substances within a laboratory. These impellers mixed fluids in significantly less time and used a lower amount of power compared to other commercially available mixing blades. Both experimental and computational models were created under a variety of mixing conditions and impeller geometries. The result of which was a large data set from which snapshots were taken that constructed the ROM. Additionally, this data set was validated against experimental testing. It was found that different blade configurations resulted in varying mixing results depending on the fluid (Yu et al. 2012). Different geometric ratios of the KDM were identified as having the largest effect on the resultant mixing times. The first being the diameter of the impeller over the diameter of the fluid vessel (D/T), then the submergence of the KDM in the mixing fluid to the diameter of the KDM (s/D) and finally the off bottom clearance of the impeller compared to the KDM diameter (c/D). The research goes on further to recommend other geometric ratios of the KDM impeller that have been found to be optimal, such as the

length of the KDM compared to the diameter of the KDM, which should be 1.0. The number of blade elements could be increased beyond two as long as these other ratios were held constant, but for the purpose of this case study two elements were chosen as the dominate design basis. Additionally, any of these geometric ratios could have been investigated in the case study, but we chose to focus on D/T because the other ratios seem to focus more on the conditions for which the impeller was operated at. From Yu et al. (2012) it was found that a D/T ratio of around 0.6 results in the best performance characteristics for the entire range of operating conditions. These operating parameters or input conditions can be seen in Table 3.1, where a range of working fluid viscosities, the rotations per minute of the impeller, and these varying D/T ratios resulted in different flow fields and thus mixing times. The CFD models that were developed for the original design of the impeller were adapted for this research, which provided the design space to search for this customized design. The exploration of this design space using ROMs allows for the design of the mixing impeller to be tailored for a refined set of mixing conditions, thus resulting in an increase in performance.

One challenge is the application of POD to a geometry change. In the past ROMs have been used to predict limited geometry changes of designs that could be defined by a single variable (Hay et al. 2010, McCorkle and Bryden 2011) or an equation to describe a curve (Suram, McCorkle, Bryden 2008, Raghavan et al. 2013), but the geometries in this research were too complicated to be defined by either method. Zonal models have been used in concert with reduced order models that improved the accuracy of results for cases of shape optimization (Iuliano and Quagliarella 2013). The results were improved because the zonal model allowed designers to focus on the effects of a design change within one small section

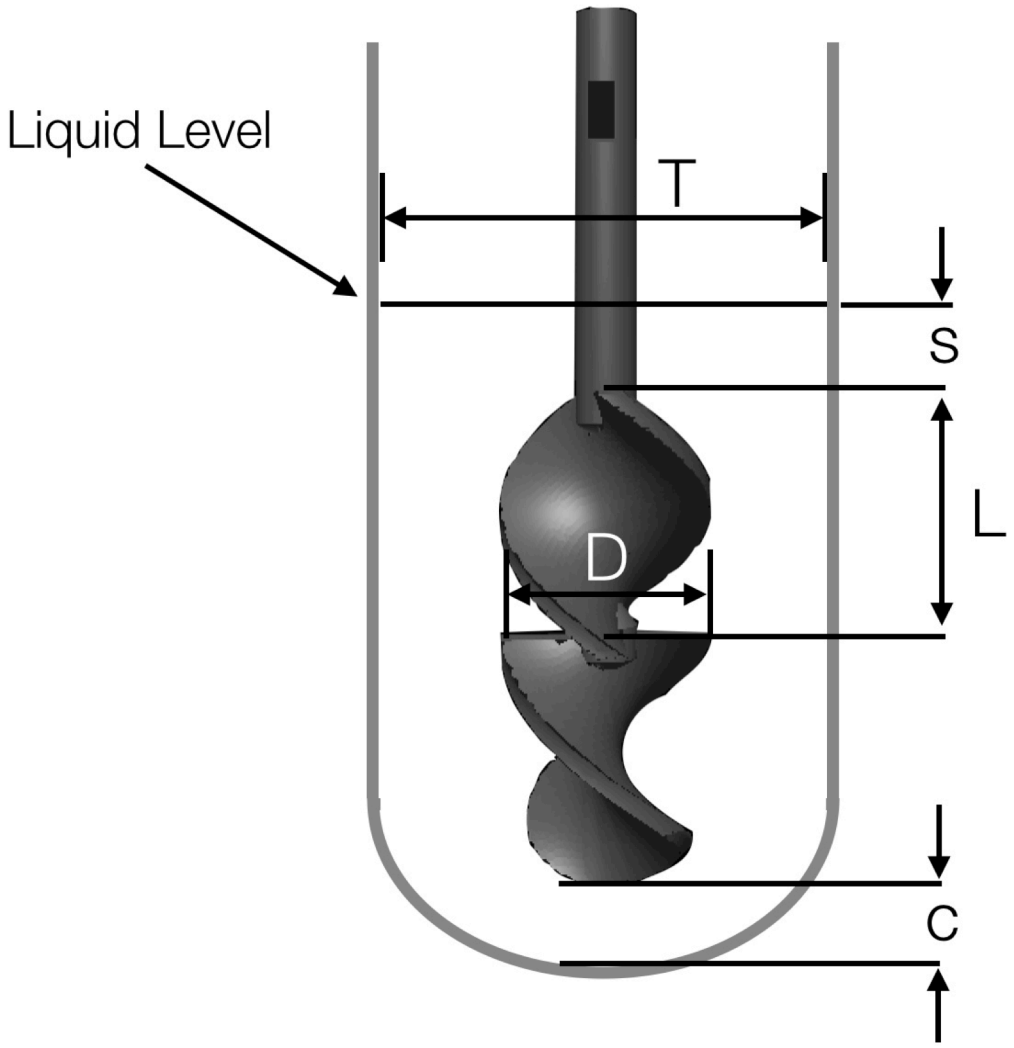

Fig. 3.4. Kar Dynamic Mixer Impeller

Table 3.1. Operating Ranges of the Mixer Impeller for the Case Study.

	Minimum	Maximum
Viscosity (cP)	5,000	30,000
RPM	200	600
D/T	0.33	0.85

of the entire model. Some have successfully attempted geometry changes but required models to be simplified to only simple fluid flows (Ling 2013) or two-dimensional profiles (Toal et al. 2010). Other methods for shape optimization have been used to develop mixing impellers for centrifugal pumps such as neural networks (Park et al. 2013, Derakhshan et al. 2013), evolutionary algorithms (Sun and Schäfer 2011), genetic algorithm (Zhang et al. 2011, Ushijima and Yeh 2013) and even evolutionary algorithms (Kim et al. 2010) that resulted in performance improvements in less computation time. This work improves upon previous research in both the shape optimization for mixing impeller design and also using proper orthogonal decomposition to predict the performances of more complex geometries than before.

The Dow Chemical Company had previously constructed the geometries and meshes for the KDM used to identify these critical parameters. Due to these varying KDM geometries, the meshes used to conduct these simulations correspondingly varied in size. Proper orthogonal decomposition requires that every snapshot inputted must have exactly the same number of nodes in the mesh. In order to overcome the variance in mesh size, a uniform mesh size was defined. The meshing program ICEM was used to accomplish these modifications of adapting all meshes to the universal mesh size (ICEM 2013). The new mesh while similar to the original mesh did not have the simulation data associated with it from the CFD simulation. Computing all of the simulations for this universal mesh size again would be impractical for this workflow, thus eliminating many of the benefits presented. Instead the resultant simulation data from the original mesh is interpolated onto these universal meshes. Different techniques such as Kriging and inverse weight were investigated, but ultimately the mesh-to-mesh interpolation tool that comes standard in the Fluent CFD package proved

successful (FLUENT 2013). The tool conducts a zeroth order for interpolating the solution data from one mesh to another. The results from this interpolation and the rest of the comparisons for y-velocity seen in this research are displayed in the same way to allow for comparison between different parameters. The first result seen is the L2 norm of the flow field between the high fidelity model simulated using computational fluid dynamics and the results of this research either from the interpolation techniques or the use of reduced order modeling. Then these flow fields are examined further about two different planes for which y-velocity profiles are shown. The first y-velocity profile seen is from Fig 3.5a, is a negative y-direction velocity over a much larger area. The second plane for which the y-velocity profile is orthogonal to the first plane taken from is displayed in Fig. 3.5b, which is over a much smaller area (the outside edge of the impeller) but has the highest y-velocity magnitudes. There was a need to examine multiple planes within the flow field because this overhead mixing impeller creates non-axial directional flow such that the flow fields varies throughout the environment. Other planes and parameters were investigated throughout the flow fields, and techniques but within this thesis two planes of investigation are shown along with the L2 norm of the flow field is displayed to convey the accuracy of these presented methods. The results of this interpolation, shown in Fig. 3.6, show the y-direction velocity of the original case overlaid with the interpolated case along a line within the impeller. Figure 3.7 shows the y-velocity profile upon the orthogonal plane as seen in Fig. 3.5b with the interpolated and CFD simulated data sets having almost identical flow fields. The average relative error between the two is less than 0.5%, which can be seen also in how similar the data points are between the two y–direction velocity profiles.

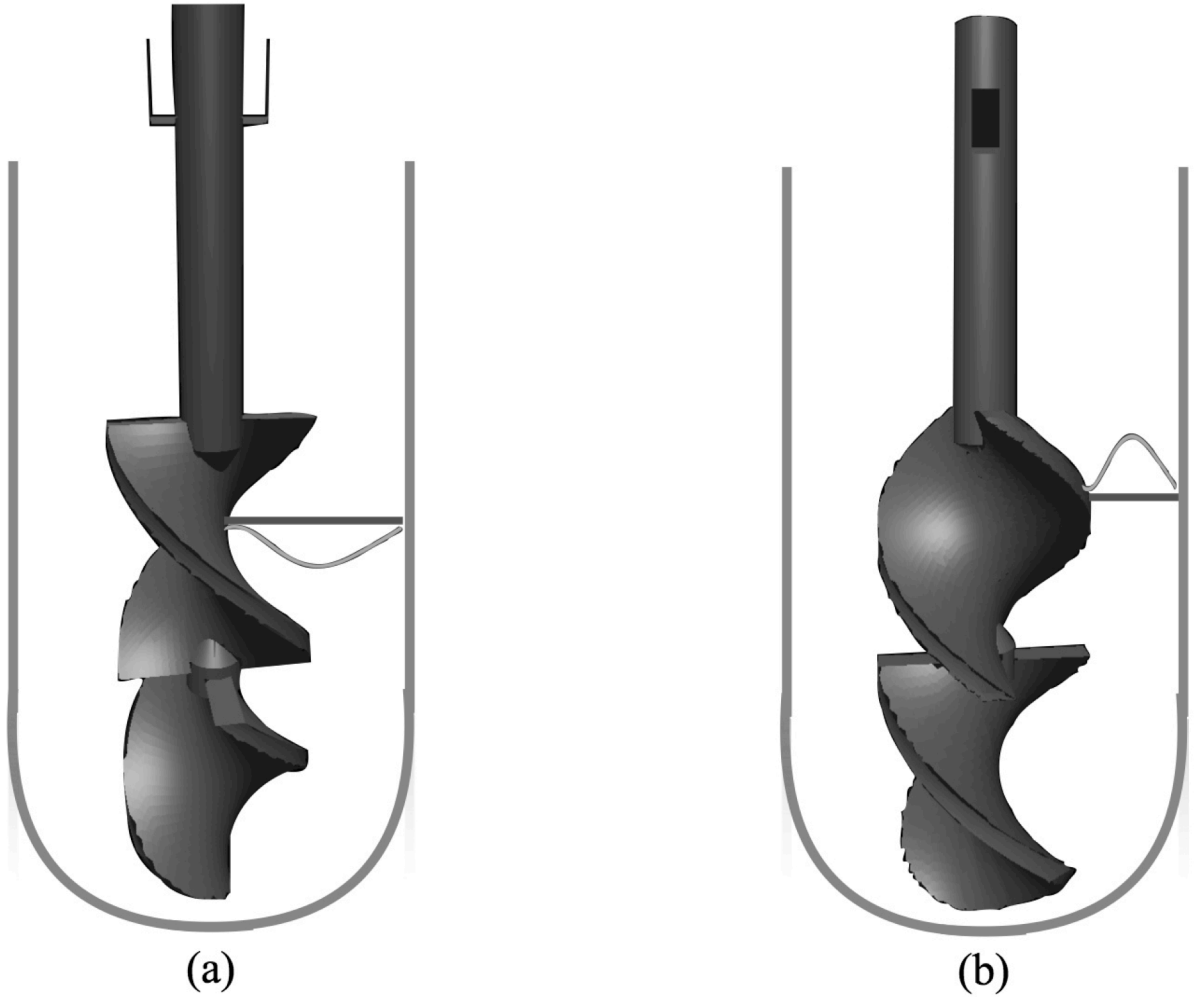

Fig. 3.5. Planes within the Flow Field Used for Comparison (a) The First Plane About which Measurements are Taken. (b) The Second Plane About which Measurements are Taken is Orthogonal from Plane A.

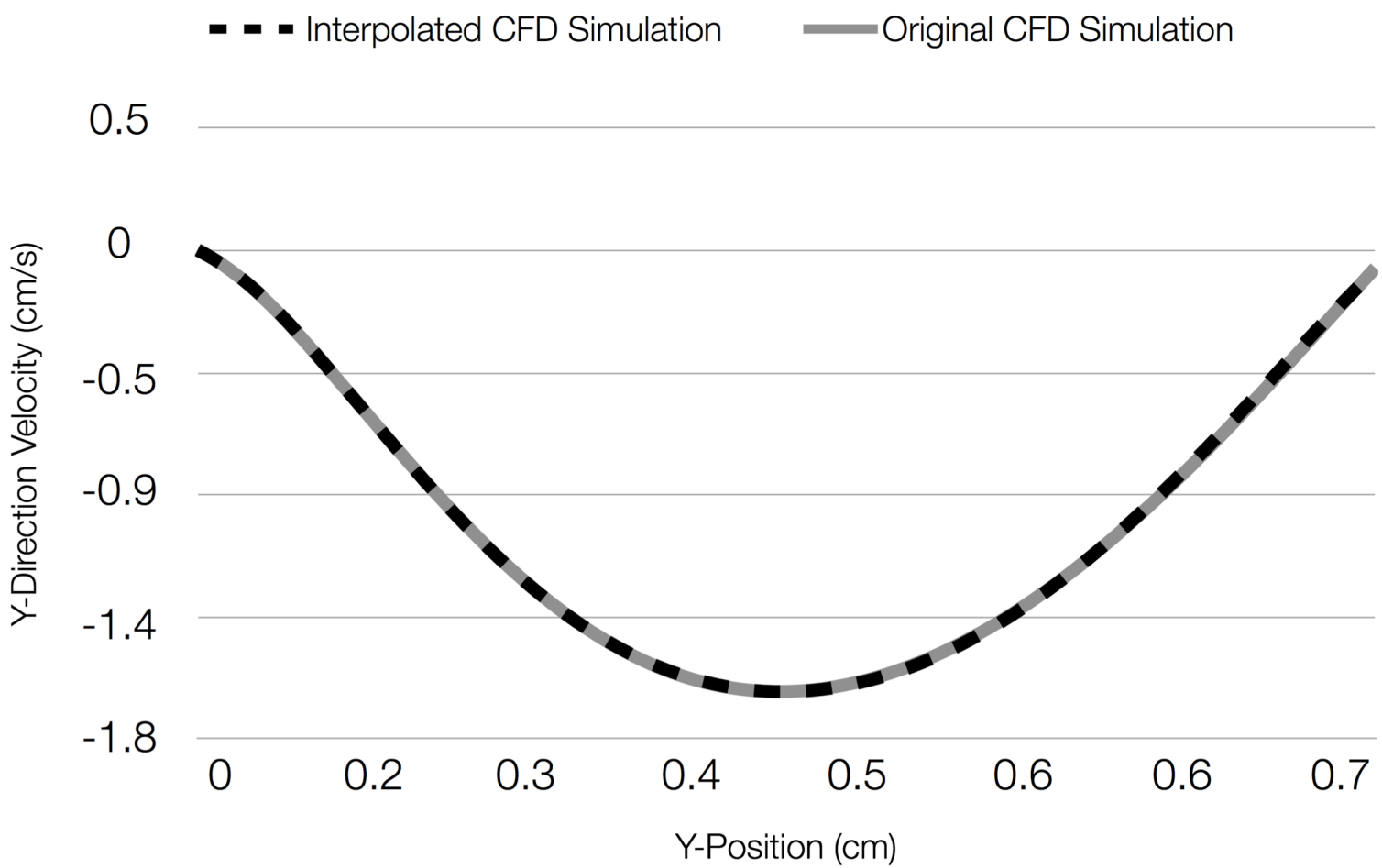

Fig. 3.6. Interpolation Comparison for Universal Mesh

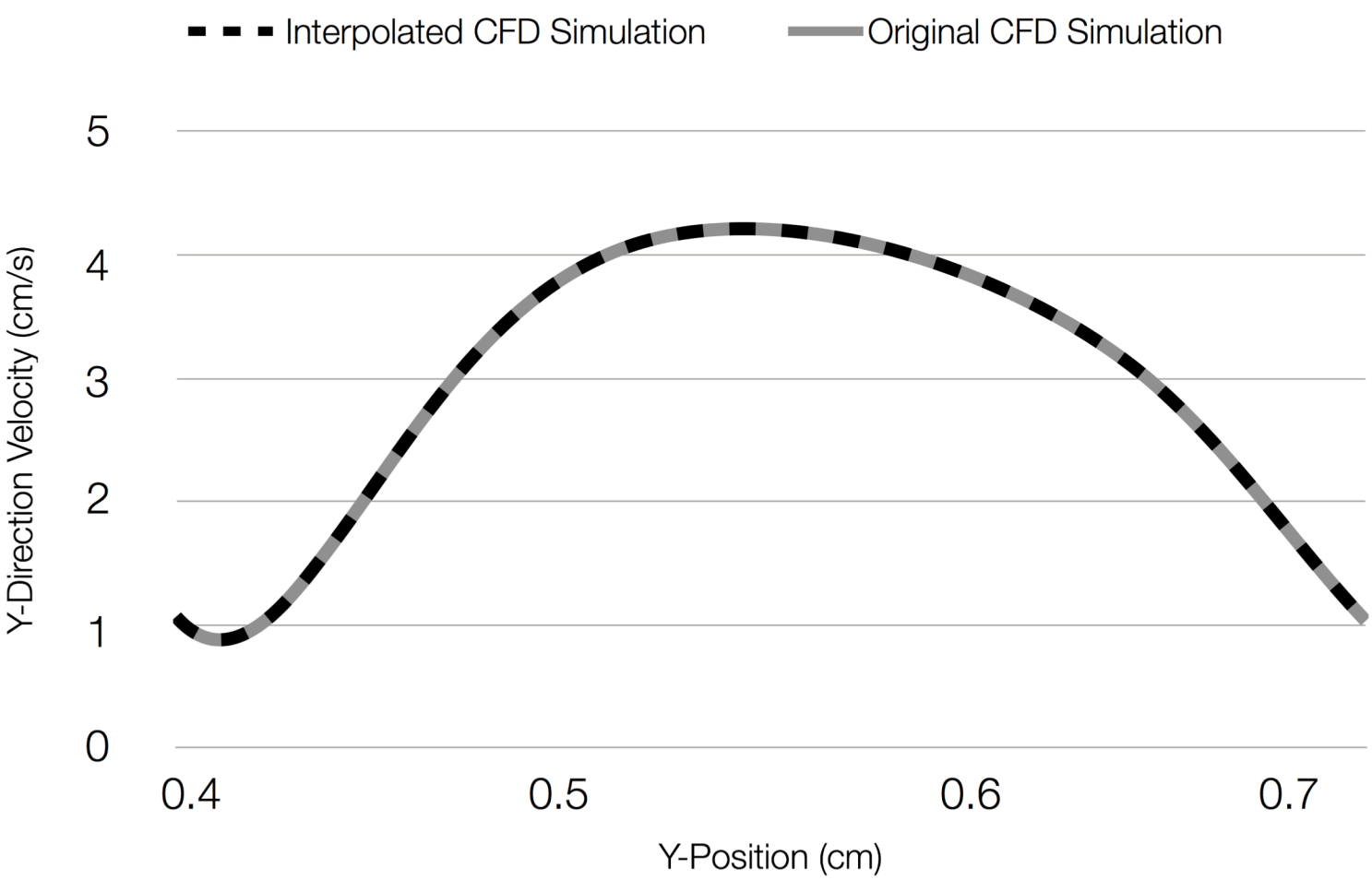

Fig. 3.7. Interpolation Comparison for Universal Mesh on Orthogonal Plane

3.5 Discussion of Results

The process of integrating detailed analysis into the conceptual and preliminary design phases began with validating reduced order models against simulation and experimental data to determine their accuracy. Without an acceptable accuracy there is little chance that designers would want quick yet inaccurate simulations as opposed to time consuming accurate simulations. In order to determine the accuracy of ROMs in the case of the KDM impeller, results were separated into three sections: constant geometries, varied geometries, and varied geometries with associated mixing time. Previous research has shown that using ROMs to simulate independent variables for constant geometries such as velocity have generated accurate results. The outputs of a ROM are based upon its predictions for a queried set of parameters. In this research the parameters used were the rotations per minute of the KDM impeller and the viscosity of the working fluid, which previously has been shown to have the largest effect on the mixing times of the KDM impeller from the experimental research by Yu et al. (2012). The outputs of the ROM can be any property of the CFD simulations used to construct the ROM, and for this research velocities in the x, y, and z directions along with magnitude are investigated and used for comparison. These properties were chosen because designs were being searched for with the smallest mixing time, and y-velocity is a good indicator of this result. Then a geometric parameter was added defining the ratio of the diameter of the KDM impeller over the diameter of the mixing vessel (D/T). Finally, the total time each fluid took to be mixed under each scenario of viscosity, rotations per minute, and the D/T ratio was inputted to the ROM. The addition of time could now be used to search for an improved design that resulted in a lower mixing time given these other defining parameters.

Initial tests were conducted that determined the accuracy of a reduced order model for the specific case of the KDM impeller using two independent parameters of a constant D/T. A small number of snapshots were used to construct an initial ROM that defined the design space. Four snapshots defined the boundaries of the design space and one snapshot defined the average parameters. One test that was initially conducted ensured the reduced order model's precision by a query for a set of parameters from a snapshot used to construct the ROM. A L2 norm of 0% was found which was expected because the reduced order model had a complete understanding of the flow field for this snapshot. This test proved beneficial because it displayed the ROMs understanding of the design space and the cases used to construct itself. The L2 norm was computed by comparing a corresponding CFD simulation of the flow field for the same operating conditions for which the ROM was queried.

Reduced order modeling has shown success when predicting the flow fields using operating conditions to define each snapshot while maintaining a constant geometry. The results seen in this research echo this success through the implementation of the technique in this case study. Also, the geometry was held constant for the exploration of this design space in order to validate the design workflow for this case study. The Dow Chemical Company provided a collection of simulated mixing results for a wide range of mixing conditions within the designs' operational range. Using these snapshots, a ROM was constructed using the five most extreme operating conditions that defined the design space. It was important to be able to explore the design space fully and understand how many snapshots were needed for an accurate prediction. The reduced order model of five snapshots was then queried for the same operating conditions (rotations per minute and viscosity) as the validated test case. The L2 norm between the simulated test case and the predictions from the ROM was 54.0%,

as shown in Table 3.2. Additional snapshots were then added to the ROM, increasing from five snapshots to eleven, thus reducing the L2 norm to 2.5%. The L2 norm for this ROM then remains constant to 2.5% from adding five more snapshots for a total of sixteen snapshots. The result of these five additional snapshots did not help define the design space further for the queried case. However, these high fidelity models still had value because they provided the ROM with more information about the design space so future queries for a different set of parameters would benefit from this information. It was important to investigate areas within the flow field and compare the velocity profiles of varying planes for the ROMs of different sizes and the test case. Velocity profiles along a plane are then selected from the flow field to further examine this accuracy from the ROM seen in Fig. 3.8. The velocity profiles confirm the results with the y-velocity profile becoming closer to that of the test case. Also, even though the five-snapshot ROM did not provide the same magnitude as the test case, it had a similar y-velocity profile. The similar profile allows designers to make engineering decisions for what direction to further investigate with this workflow and what areas of the design space need further information. The y-velocity profiles of the flow field from an orthogonal plane are displayed in Fig. 3.9. These results show profiles of a much higher magnitude over a smaller area noting the x-axis begins at 0.4 centimeters instead of 0.00762 centimeters seen in Fig. 3.8. This is due to the results taken on the edge of the mixing impeller blade. But this different view of the results shows an improvement in accuracy from additional snapshots and the identical flow fields that resulted from eleven and sixteen snapshots. The results of using reduced order modeling for this case study of a constant mixing impeller geometry proved accurate. The speed at which these results were obtained was a matter of seconds, thus allowing the design space to be quickly and accurately searched.

Table 3.2. The L2 Norm of the Flow Field is the Result of the Number of Snapshots Used to Construct Reduced Order Models of a Constant Geometry of the Impeller.

Number of Snapshots	L2 Norm
5	54.0%
11	2.5%
16	2.5%

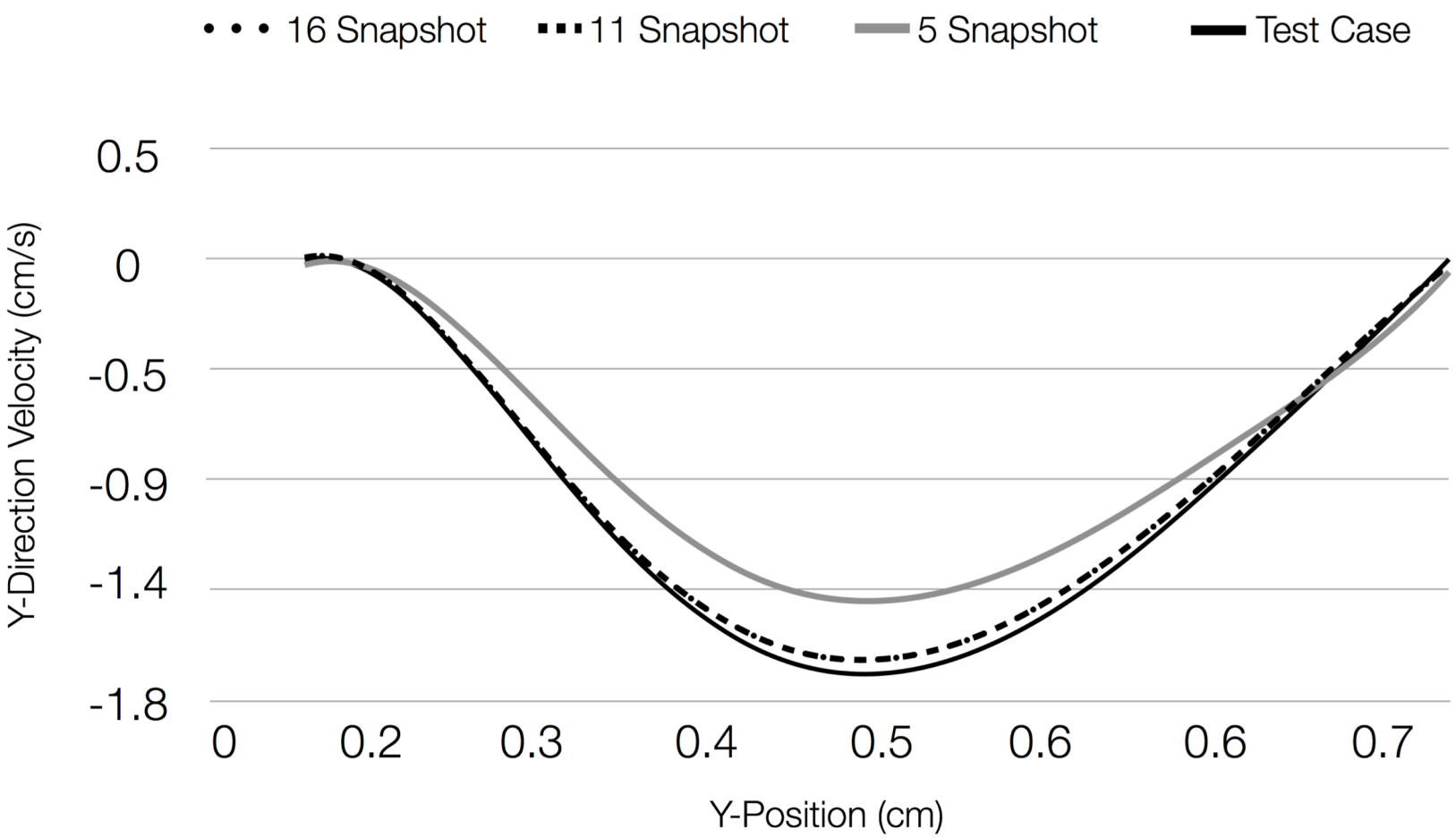

Fig. 3.8. Y-Velocity Profile of Reduced Order Models of a Constant Geometry vs. the Test Case

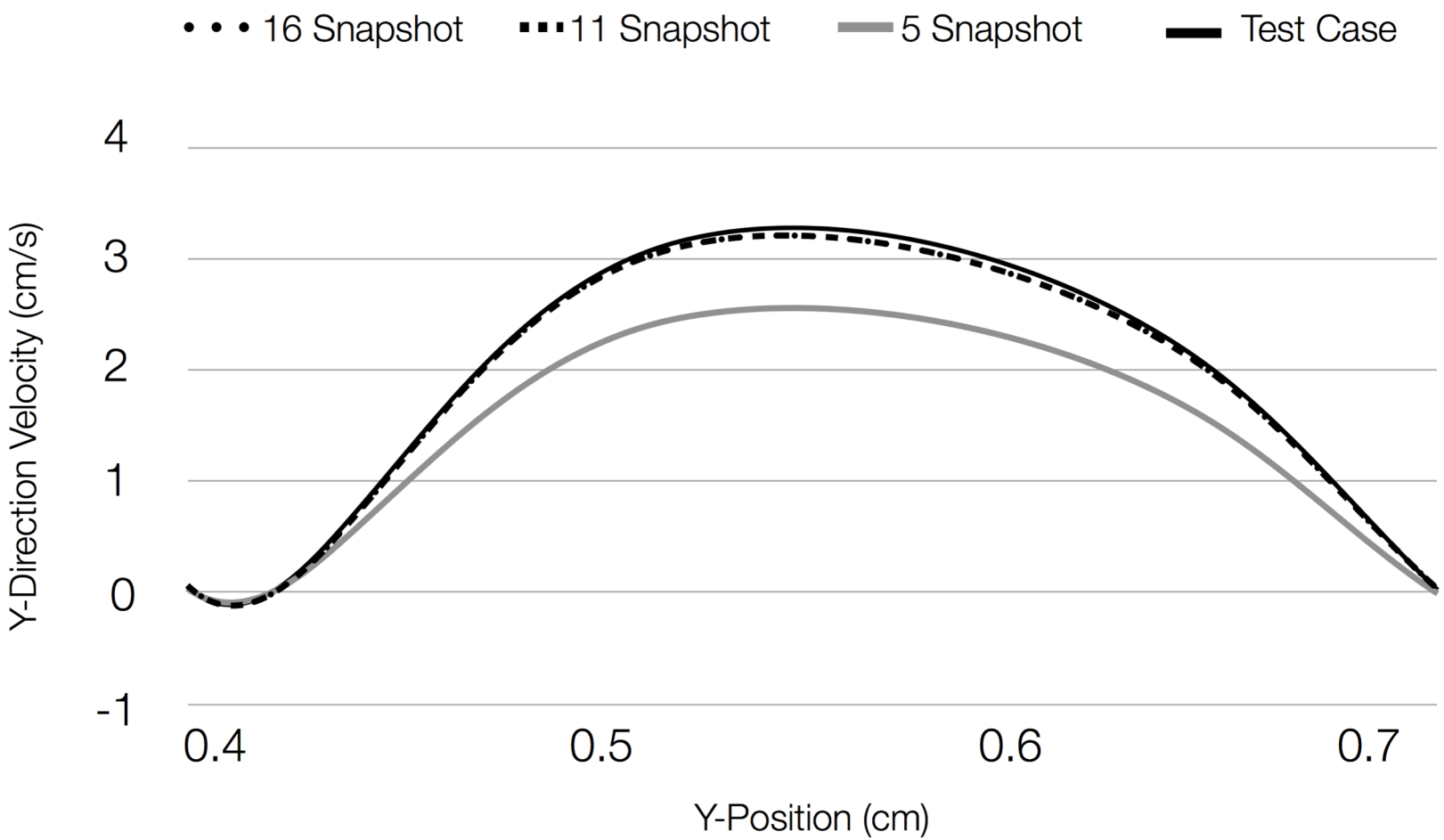

Fig. 3.9. Y-Velocity Profile of an Orthogonal Plane of Reduced Order Models of a Constant Geometry vs. the Test Case

The next step in this research was examining the additional input parameter of varying the impeller geometries, D/T. Using the universal mesh technique developed for this research, these geometry changes of the overhead mixing impeller could be investigated. The process began similar as with the cases of constant geometry where a small number of cases are used to define the design space. These geometric snapshots were defined using the D/T ratio and the rotations per minute of the mixing impeller. Again as the design space was better understood, more focused information could then be added to the ROM. A similar decrease in L2 norm was seen moving from five snapshots to sixteen snapshots. The investigation of the geometry is much more difficult because small geometry changes result in a wide variation of flow fields. This is illustrated by the L2 norm, shown in Table 3.3, for five snapshots being greater in the similar sized ROMs of constant D/T. Figure 3.10 shows the y-velocity profiles of the flow fields along a plane. The difference between the test case and the five snapshot ROMs are markedly different, but with eleven and sixteen snapshots similar y-velocity profiles result. Figure 3.11 shows the y-velocity profiles along an orthogonal plane with similar results.

Table 3.3. The L2 Norm of the Flow Field is the Result of the Number of Snapshots Used to Construct Reduced Order Models of Varying Geometry of the Impeller.

Number of Snapshots	L2 Norm
5	161.9%
11	39.0%
16	5.2%

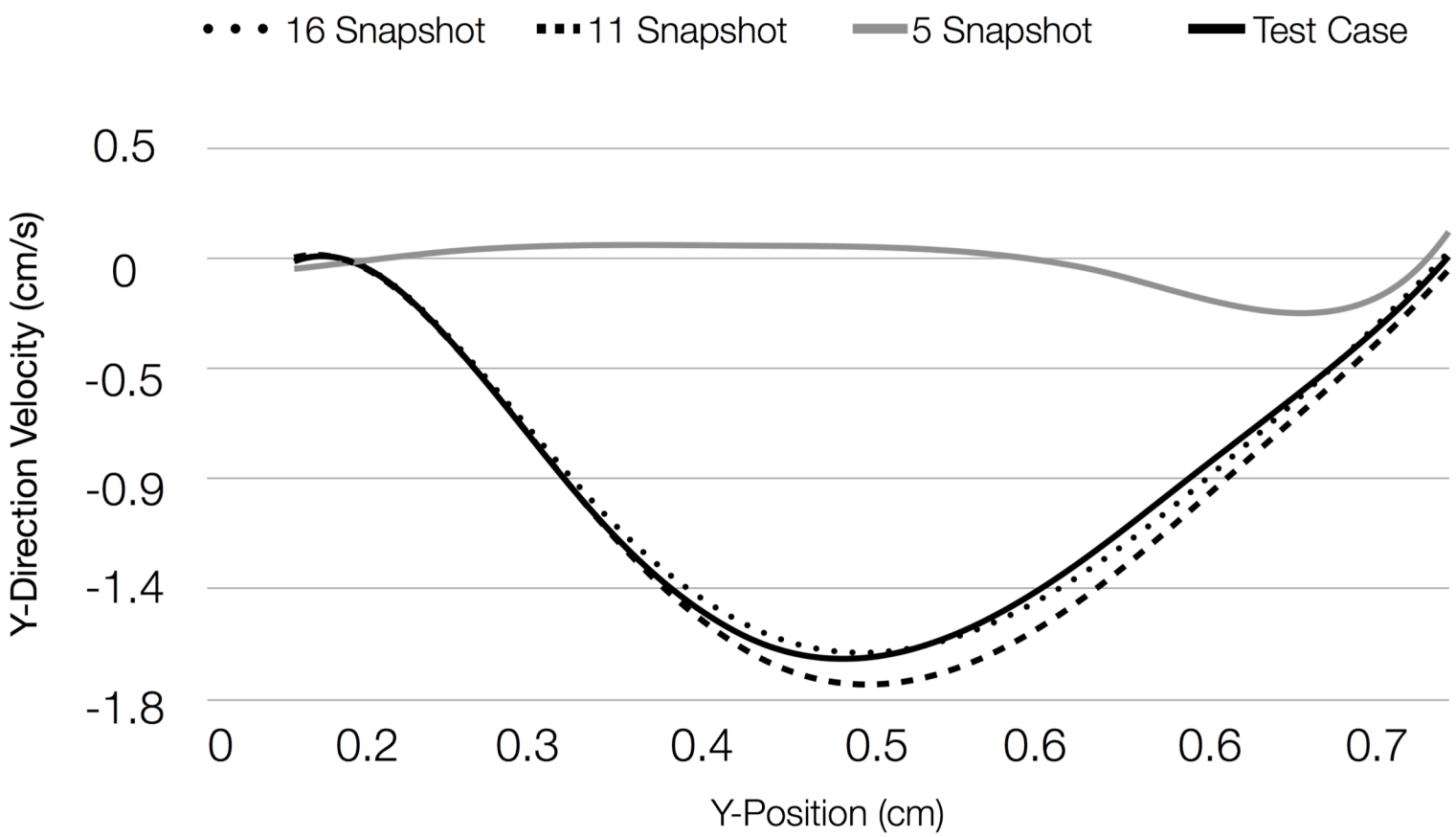

Fig. 3.10. Y-Velocity Profile of Reduced Order Models of a Varied Geometry vs. the Test Case

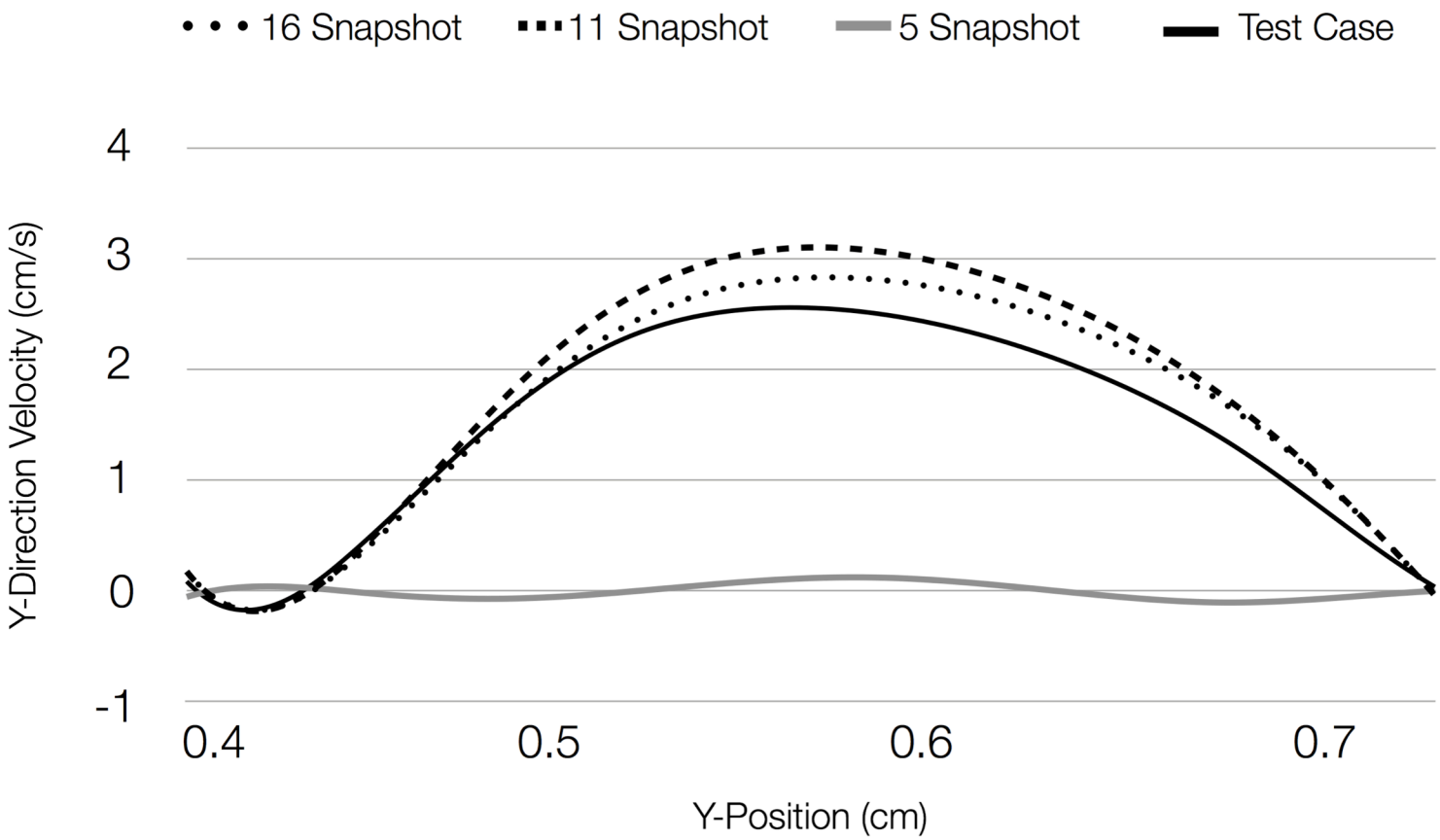

Fig. 3.11. Y-Velocity Profile of an Orthogonal Plane of Reduced Order Models of a Varied Geometry vs. the Test Case

After investigating the input parameters for the mixing impeller, the output parameter, which is mixing time, was investigated. This parameter was the most important since the goal of the designs was to reduce mixing times over other mixing impellers. For this research mixing time is t_{95}, which is the time required for the solution to become 95% mixed. The snapshots defined by the mixing time and D/T. These two parameters were chosen because the purpose of this research was to search the design space for geometries that further reduced mixing time. The construction of the ROM begins in the same way as for investigating other parameters with a few snapshots defining the design space and with more snapshots added to improve the amount of knowledge about the design space. A similar progression in a reducing in the L2 norm, shown in Table 3.4, occurs moving from 98% with five snapshots to 3% with sixteen snapshots. It is interesting to note that the reduction in L2 norm resulting from between five and twelve snapshots is minimal, but in Fig. 3.12 and Fig. 3.13 it is seen that the y-velocity profile does change between the two with the snapshot ROM having a similar profile to the test case but overshooting the magnitude. Using the Kar Dynamic Mixer impeller as a case study, different input and output parameters were investigated and used to define and accurately predict results.

Table 3.4. The L2 Norm of the Flow Field is the Result of the Number of Snapshots Used to Construct Reduced Order Models Using the Mixing Time for the Impeller for Varied Geometry.

Number of Snapshots	L2 Norm
5	98.1 %
12	90.2%
16	3.3%

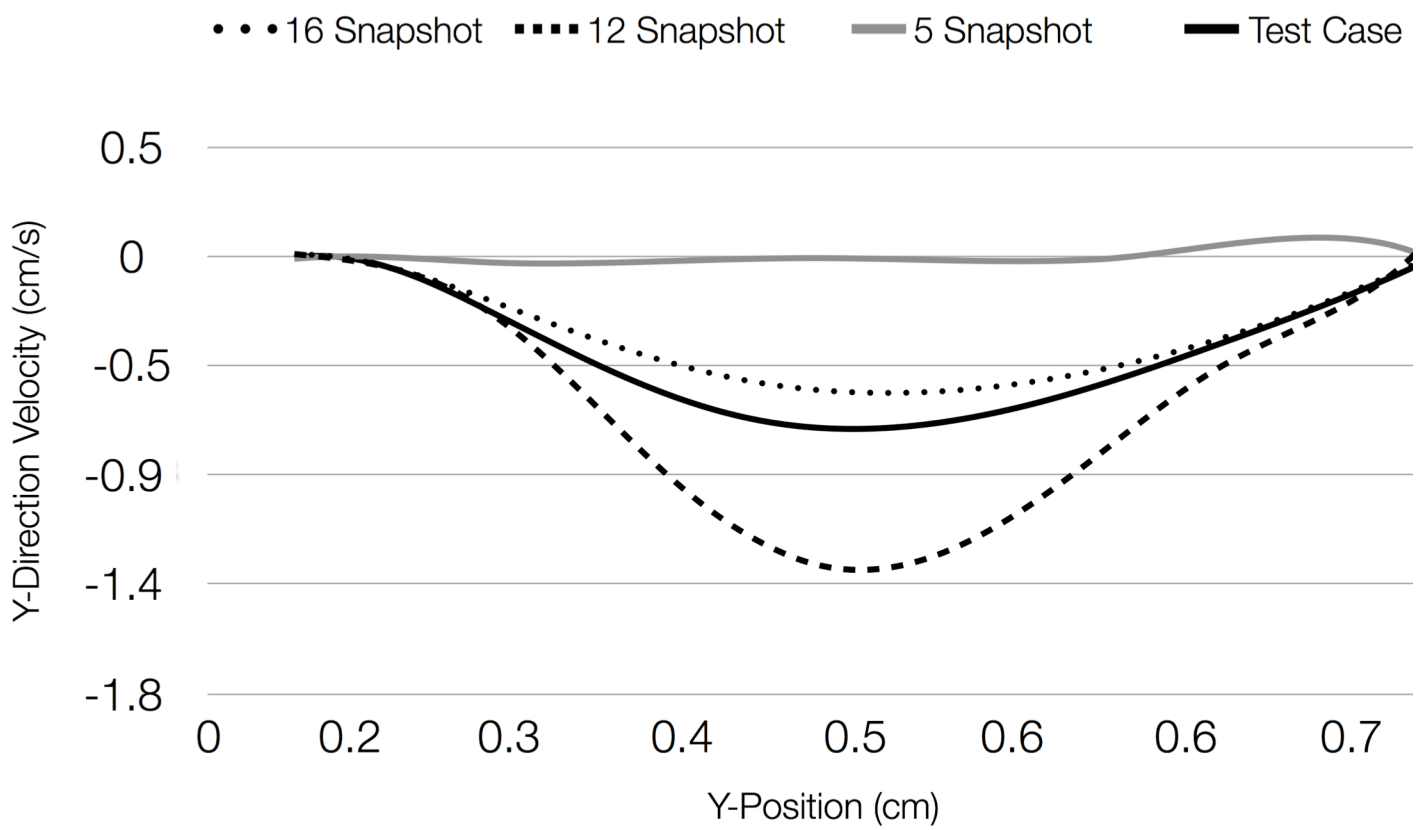

Fig. 3.12. Y-Velocity Profile of a Reduced Order Model using the Mixing Time for Varied Geometry vs. the Test Case

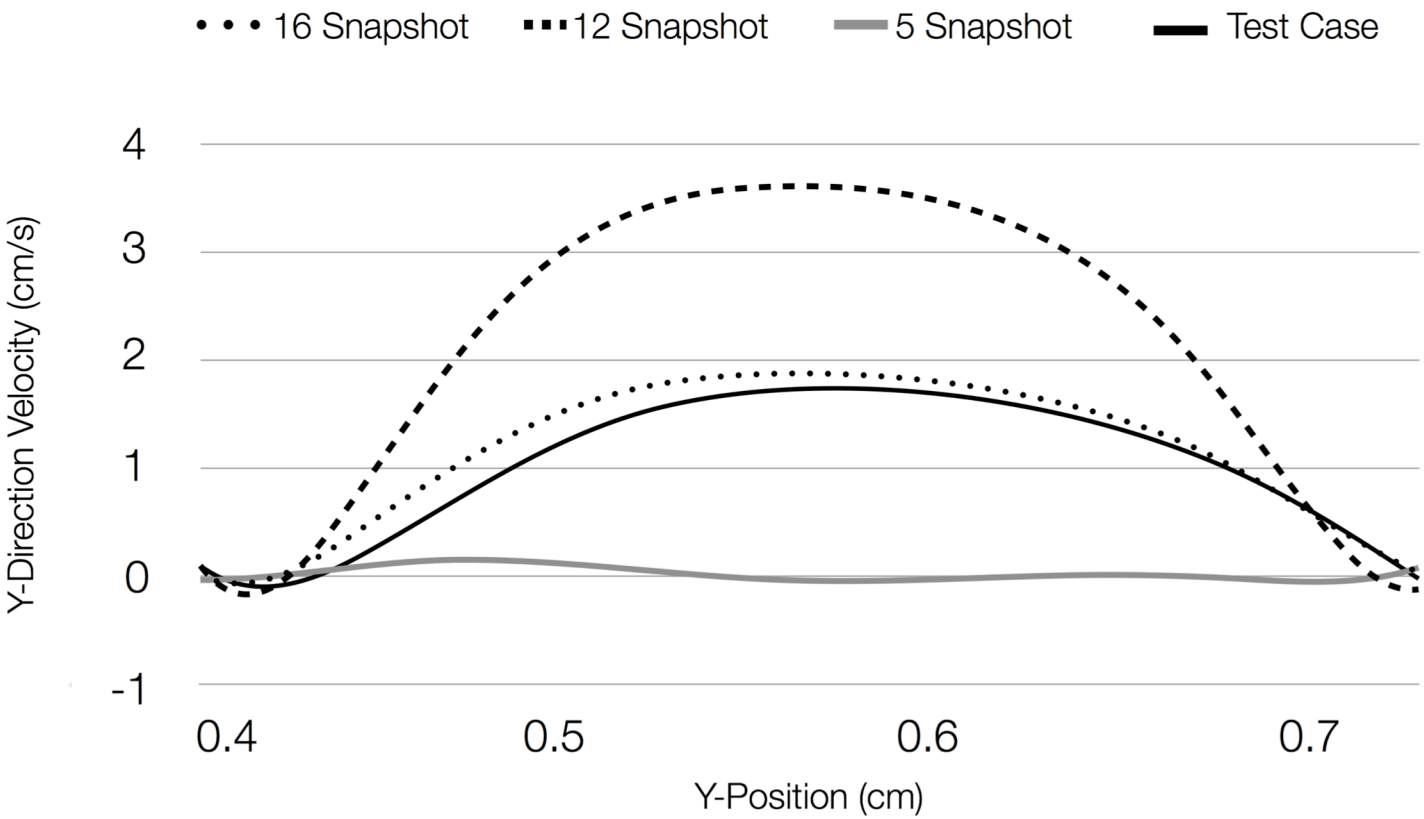

Fig. 3.13. Y-Velocity Profile of a Reduced Order Model of an Orthogonal Plane Using Mixing Time for Varied Geometry vs. the Test Case

With this information the design space was then searched for a customized design that would show improved performance for a refined set of operating conditions. The improved performance would be a further reduction in mixing time, and the customized design would be a D/T ratio that differed from the known optimum for the entire design space. The ROM enables the researchers to quickly explore the design space. Due to this speed, a large number of designs were considered. One design was found that accomplished this goal. A D/T ratio of 0.57 was identified to have 7-8% improvement in mixing time for RPMs under 300 and working fluid viscosities under 10,000 cp. This geometry improves upon the global best D/T ratio, 0.6, of the larger range of operating conditions. So for the small subset of the design space, an improved customized geometry was identified and confirmed using high fidelity modeling. Using this design it could quickly be made using digital manufacturing for an instant performance improvement. The power of coupling reduced order modeling and digital manufacturing is illustrated in this research by how simple it was to identify a design in an inexpensive and reduced timeframe.

3.6 Conclusions and Future Work

This research proposes a revised engineering design workflow to amplify the power of digital manufacturing. Using this design workflow developed to take advantage of the benefits of digital manufacturing, customized products can be manufactured at little to no cost in a reduced time frame. This level of customization enables designers to develop products for a refined set of operating conditions that result in improved performance characteristics. The customization of a design for this refined set of parameters builds upon already established designs such that a collection of high fidelity models exists from the established design development. Although manufacturing technologies have seen rapid

advancement in capabilities, the design process workflows used to develop these products have not followed a similar path of advancement. As a result, the disparity in timescales between the design process and manufacturing continues to expand. The design workflow developed and implemented in this research overcomes these disparate timescales through the utilization of reduced order modeling. Reduced order models couple the information developed in the three phases of design along with the ever-improving model of the design's performance within its design space. Additionally, in this implemented design workflow much of the detailed modeling is shifted earlier in the design process from the detailed phase and into the conceptual and preliminary phases. This result in an improved model of the design space focusing on these customized conditions. Reduced order models are a powerful tool that allows designers to explore the design space at timescales orders of magnitude less that that of high fidelity modeling. A design case study using the Kar Dynamic Mixer impeller was then used to implement the proposed design workflow. The ROM accurately predicted the flow fields for a variety of mixing conditions under various geometries. Because the mixing impeller had previously been developed, a large number of high fidelity models already existed, thus limiting the amount of additional high fidelity simulations needed to develop the customized design. This reuse of these expensive and time-consuming high fidelity models amplifies their value. These models are then used to construct the reduced order model, thus defining the design space for which collaborators can query for this customized design. The ease at which the design space was explored allowed for varying geometries to be investigated for certain mixing conditions. One example was found for a customized geometry for a refined set of mixing conditions that resulted in a 7-8% reduction in mixing time, a critical indicator of impeller performance.

The next steps for this research are integrating these tools into one seamless virtual engineering environment. In such an environment the designers, engineers and collaborators would all be working within a design environment with ultra high definition displays and digital manufacturing tools. The result of this would allow this group of stakeholders to quickly explore the design space and manufacture these customized designs without ever leaving the design environment. Specifically, within the software the visualized flow field will be instantly updated as the geometry changes with easy to use user interfaces using elements such as sliders to vary different geometric ratios.

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CHAPTER 4

CONCLUSIONS AND FUTURE RESEARCH

This thesis extended the use of detailed analysis tools such as computational fluid dynamics into the conceptual and preliminary design phases. As a result, a larger collection of designs could be considered quickly and accurately to result in an improved design. This was achieved by using proper orthogonal decomposition to create reduced order models. To implement these analysis tools, the engineering design workflow commonly known as abstraction-to-detail was altered to be included into its framework. The capabilities of reduced order models were also extended in this research to include the ability to predict geometry changes of the complicated geometries of the KDM impeller. While this work proved successful for the case study presented in this research, it is applicable to any design process workflow where detailed analysis is involved. Additionally, the mixing time needed to achieve a mixed fluid was also used as a parameter for the ROMs. Encompassing these two types of parameters allows designers to understand the effects of a wide array of geometries and mixing conditions. The result of this work enables designers, analysts, and stakeholders to consider the entire design space on the path to an improved customized design.

From this research the future work that has been identified for further research focuses on the finer details for the better management and display of information. The organization of ROMs would allow designers and analysts to continually update both the design and analysis simultaneously, thus allowing all stakeholders to have access to the complete set of ROMs. Also, this would eliminate the need for the ROMs to be reconstructed when additional snapshots and information is added. Secondly, these ROMs should then be

integrated into one integrated design environment. This integration would then allow all collaborators to be able to start from a problem definition and move through the design process until one final design is achieved without ever having to leave the computational environment.

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