DISSERTATION

METHODS FOR ADVANCING AUTOMOBILE RESEARCH WITH ENERGY-USE SIMULATION

Submitted by

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In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2014

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ABSTRACT

METHODS FOR ADVANCING AUTOMOBILE RESEARCH WITH ENERGY-USE SIMULATION

Personal transportation has a large and increasing impact on people, society, and the environment globally. Computational energy-use simulation is becoming a key tool for automotive research and development in designing efficient, sustainable, and consumer acceptable personal transportation systems. Historically, research in personal transportation system design has not been held to the same standards as other scientific fields in that classical experimental design concepts have not been followed in practice. Instead, transportation researchers have built their analyses around available automotive simulation tools, but conventional automotive simulation tools are not well-equipped to answer system-level questions regarding transportation system design, environmental impacts, and policy analysis.

The proposed work in this dissertation aims to provide a means for applying more relevant simulation and analysis tools to these system-level research questions. First, I describe the objectives and requirements of vehicle energy-use simulation and design research, and the tools that have been used to execute this research. Next this dissertation develops a toolset for constructing system-level design studies with structured investigations and defensible hypothesis testing. The roles of experimental design, optimization, concept of operations, decision support, and uncertainty are defined for the application of automotive energy simulation and system design studies.

The results of this work are a suite of computational design and analysis tools that can serve to hold automotive research to the same standard as other scientific fields while providing the tools necessary to complete defensible and objective design studies.

ACKNOWLEDGEMENT

Completing this Dissertation and Ph.D. has been a long-standing goal of mine. Over the years I have gained tremendous experience that have developed both my professional and personal life. Although much time and effort has been put forth on my part, none of this would have been possible without the support of my family, friends, coworkers, and mentors.

First, I would like to acknowledge my primary faculty advisor, Dr. Thomas Bradley. Beginning at the very first moment of my graduate school career, Dr. Bradley has continuously provided me with endless resources, motivation, knowledge, and support towards obtaining my goals. I know that the dedication he has given towards my growth and development is the key enabler for every portion of the work presented in this document. I am extremely fortunate to have had Dr. Bradley as an advisor, colleague, and friend and can never thank him enough.

Second, I would like to acknowledge my coworkers and friends who have provided me with the necessary work/life balance to maintain a reasonable level of sanity and health. Although you are too numerous to list here, if you are reading this and wondering if I am talking about you; I probably am. I give you my sincere thanks and look forward to seeing all of your lives continue to enrich the world around you.

Finally, I would like to acknowledge my family, particularly Mom, Dad, and Sis. The emotional drain associated with dedication to work such as this dissertation would be insurmountable if not for you. Your encouragement, support, and advice will continue to guide me throughout my life. I love you all.

Thank you,

-Ben

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1 Background

Personal transportation contributes positively to society through accelerated mobility of knowledge and goods as well as freedom to travel where and when desired. The improved standard of living associated with personal transportation comes at the cost of increased energy consumption and pollution. In the United States the demand for and affordability of personal transportation has led the transportation sector to be the largest greenhouse gas emitting sector as shown in Figure 1. Of the four primary sectors, the transportation sector has the second highest energy consumption; exceeded only by the industrial sector and followed by the residential, and then commercial sectors. Due to the large market for personal automobiles and the high impact that transportation has relative to other sectors, it is important for researchers to continue to advance vehicle technology efficiency.

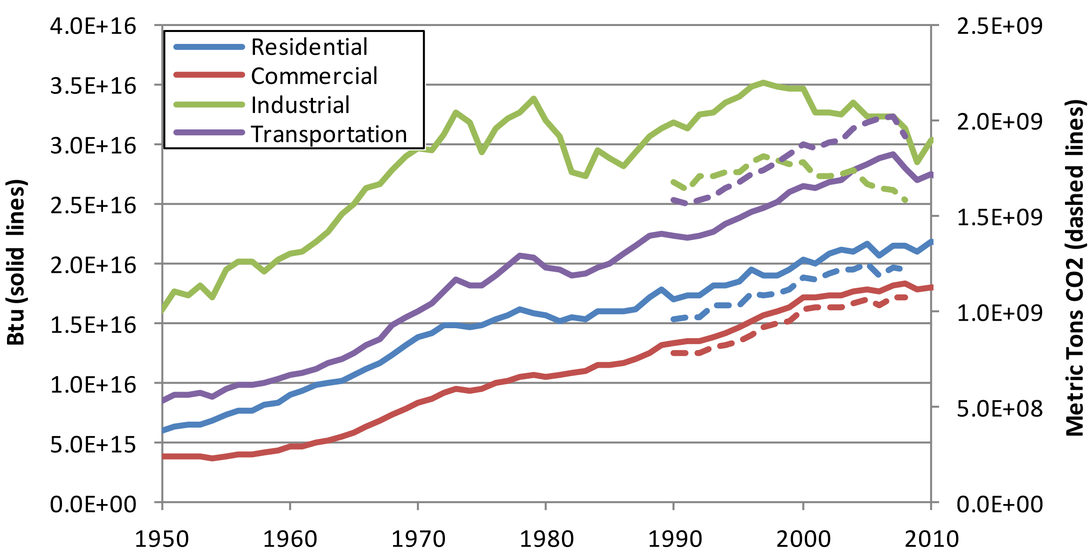

Figure 1 Energy consumption (solid lines) and CO_2 emissions (dashed lines) by sector in the United States.

This research is focused on the research and design of passenger vehicles. Passenger vehicles are classified as “any automobile (other than an automobile capable of off-highway operation) which the National Highway Traffic Safety Administration (NHTSA) [11] decides by rule is manufactured primarily for use in the transportation of not more than 10 individuals." (Section H of EPA DOT). Passenger vehicles (light and medium duty) have consistently made up approximately 90% of the total vehicle fleet and contributed to 70%-80% of total transportation fuel use since the 1960's [15].

Regulatory policy and the focus on advanced technology development from automotive manufacturers and researchers have aided in slowing the impacts of personal transportation but additional measures are required to provide a sustainable future. Figure 2 shows how passenger vehicle Corporate Average Fuel Economy (CAFE) in the United States has progressed over time and will continue to encourage improved vehicle performance in the future. A range of vehicle and technology developments is also shown in Figure 2 [10, 13, 14]. Advancements and changes in automotive technology have led to varying degrees of improvements in performance, efficiency, and environmental impacts. In recent years the largest improvements have been shown through electrification of personal transportation and it is expected that increased use of electricity and other alternative energy sources will be necessary. Simply applying non-petroleum based fuels to transportation alone without advancement in the vehicle design as a whole will likely limit the possibilities for passenger automobile improvements.

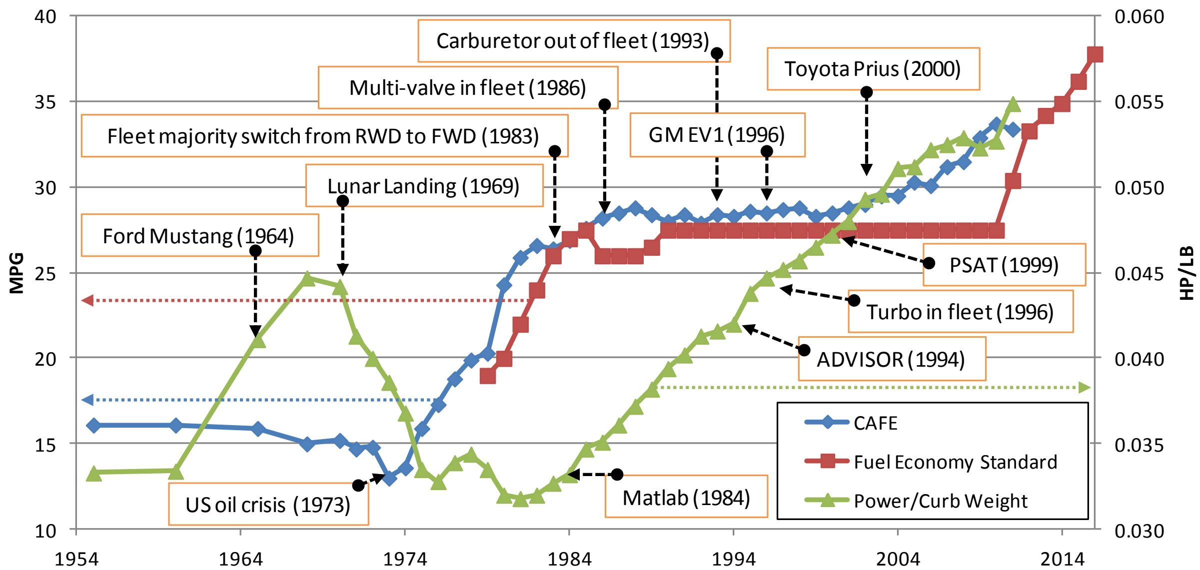

Figure 2 Timeline of US passenger cars with technology milestones.

Increasing amounts of resources are typically required for development as technology approaches theoretical operation limits for power, energy and efficiency [12]. The optimality of the design and the design progress becomes more and more important as a technology matures. The vehicle design process has become more of a systematic engineering design process in order to meet the increasingly stringent design requirements of modern automobiles. The system engineering processes provide structure in an effort to reduce redesign or failure, thus reducing development costs. As the cost, impact and demand for transportation continue to increase it becomes more important for systematic processes that are capable of efficiently producing robust vehicle designs. Vehicle research and design has been occurring since the 1800's with methods that have continuously advanced to match these demands. Many researchers have attempted to quantify and improve small portions of this process in the past [34, 17, 27] but have not reached the extent that this research proposes.

The demand for personal transportation in the passenger automobile sector, along with its associated impacts, costs, and complexities leads this research to attempt to provide a benchmark for automotive design research and guidance for future investigations. The following sections will outline the state of the field for automotive design and research, identify areas requiring improvement, propose work to fill identified areas, and provide an overview of work done to-date.

2 State of the Field

Emissions increase with the number of vehicles on the road and decrease with technology improvements aimed at increasing efficiency and decreasing emissions [138]. As populations continue to grow, more people demand transportation; 90% of which is supported by light duty vehicles (LDV) [10]. The high use of LDV leads to a focus on these vehicles for this research. Energy use simulation has been identified as an important means for improving the design and analysis of LDV.

Simulation of passenger vehicles is an important system engineering process used to perform design, analysis, and evaluation [6, 138, 115, 81, 34]. Models used in energy-use simulation are created as computational mathematical emulations of systems. Models and simulations of passenger vehicles allow researchers to study vehicle operation without requiring physical system presence [57, 65, 68, 69, 49]. The simulations of interest for the research presented here are primarily time-dependent approximations of operation whose purposes are to predict vehicle energy flows and consumption [34, 44]. Energy-use specific simulation focuses on power flow, operational characteristics, and interactions of subsystems and components within the vehicle system. An example of energy-use simulation is modeling fuel consumption of an engine over a defined driving pattern. A simulation such as this allows researchers to evaluate how efficiently energy is used for propulsion [34]. Energy-use simulations do not typically cover aspects that have little effect on power management such as modeling and simulation of materials properties or vehicle safety systems (e.g. airbags, bumpers, seatbelts).

A variety of modeling and simulation tools are available for performing energy-use simulation of vehicles [6, 23, 24, 27, 28]. The objectives of vehicle simulation vary greatly, requiring advanced analysis tools to provide accurate and understandable results and conclusions. Literature review shows that users commonly do not understand or correctly implement simulation and analysis tools for vehicle energy-use studies. In many cases automotive design research uses simulation tools that are not design to answer the questions that are being asked of them [18, 16, 23]. For example, simulation tools created to accurately model the energy use of vehicle architectures with a gasoline engine are not guaranteed to be extensible to advanced fuels or electrified hybrid vehicles [52].

The large amount of effort applied to energy-use simulation of vehicles without understanding of the tools leads to research and development that can be scientifically inconclusive, irrelevant, or even incorrect. The fault of these fallacies lie partially in the tools themselves, but most of the problems can be resolved through better understanding by the scientist or engineer performing the research and analysis.

3 Objective and Research Questions

To aid in understanding and implementing the methods and tools available for vehicle energy-use simulation, a set of research questions have been defined. A set of tasks is specified to aid in answering each of the research questions.

The work performed in completion of the proposed dissertation will result in providing an answer to the research objective:

Provide an application-specific, experimental method for conducting energy-use simulation of passenger vehicles.

3.1 Research Question 1

What are the characteristics of tools for vehicle energy-use simulation?

Vehicle energy-use simulations have been performed with a wide range of modeling and simulation tools. These simulation tools are created in software. Over time different tools have been developed and refined to model specific aspects of passenger vehicles in an effort to predict physical operation of products. Each tool has a designed set of assumptions, limitations, and applications. To build a base for investigating vehicle energy-use simulations, the tools used must be identified, analyzed, and characterized. Three tasks have been defined to identify and characterize vehicle energy-use simulation tools:

1.1 Identify the tools presently used for vehicle energy-use simulation.

1.2 Characterize simulation tools based on their formulation and application.

1.3 Use results of task 1.1 and 1.2 to determine a comprehensive application-specific set of requirements for vehicle simulation tools.

3.2 Research Question 2

What are the characteristics of tools presently used in analysis of vehicle energy-use simulation?

After the tools used to carry out energy-use simulation have been identified and characterized, the analysis tools applied to the simulation tools can be studied. Simulation tools alone are of little utility if they are not properly applied with associated analysis. Many processes and analysis tools are available for designers and researchers to use in application to passenger vehicles, a few of the underutilized tools that are important to advancing the state of the field in vehicle energy-use simulation studies are examined through completing the five tasks for research question 2:

2.1 Determine which algorithms are efficient and robust for vehicle simulation optimization

2.2 Quantify the uncertainty in vehicle simulation.

2.3 Characterize drive cycles as CONOP for vehicle simulations.

2.4 Determine the effect of fleet characteristics on vehicle simulation.

2.5 Determine the pathway for researchers to effectively apply vehicle simulation and analysis tools

3.3 Research Question 3

What is the robust, defensible, and extensible structure of a vehicle energy-use simulation and how can it be applied?

Simulation tools allow for a means of conducting theoretical vehicle energy-use study, analysis tools allow researchers to understand and apply the simulation tools appropriately. Together, the simulation and analysis tools must be implemented appropriately to perform studies using scientific methods:

3.1 Provide a qualitative overview of automotive energy-use simulation methods.

3.2 Perform a vehicle energy-use simulation study using the appropriate tools and methods.

4 Research

To answer the three research questions posed for this dissertation work, each question and its associated tasks will be thoroughly developed, evaluated, and reviewed. All sections will culminate in the synthesis of providing an application-specific experimental method for conducting energy-use simulation of passenger vehicles.

5 Simulation Tools for Automotive Energy-Use Studies (RQ1)

What are the characteristics of tools for vehicle energy-use simulation?

In the area of computer modeling and simulation there are many available programs and modeling languages from which to choose, each of them offering their own advantages and disadvantages. The primary areas of interest when dealing with large amounts of modeling and simulation is the level of detail presented within the models and the computational time necessary to run simulations. An inverse relation exists, wherein adding additional details to models requires more calculations and thus more computational effort. In an effort where hundreds or thousands of simulations may be necessary to satisfy an optimization, even slight increases in simulation time can cause large increases in overall optimization efforts. Other model and simulation requirements that are important include the ability of the program to allow for modification of the components and parameters represented and accurate calculation of the results attributes with appropriate precision.

5.1 Task 1.1 Identify the tools used for vehicle energy-use simulation.

Extensive research was performed to identify available tools for vehicle energy-use simulation. These modeling and simulation tools were developed either as purchasable, open source or custom in-house software packages. Additional tools exist beyond those listed in this section and new tools continue to be developed, particularly custom tools that are not sold or shared publically. The identified sets of simulation tools are listed in Table 1 [6].

Table 1 Simulation tools availability, developer, application and formulation

Program Name	Availability	Developer	Formulation	Application
ADVISOR	Open Source	National Renewable Energy Laboratory (NREL)	Simulink, Backward facing	Vehicle system
ADAMS/CAR	Purchasable	MSC.Software	Dynamic	Chassis
Autonomie	Purchasable	Argonne National Laboratory (ANL)	Simulink GUI	Vehicle system
CAR	Custom	West Virginia University	Four architectures, Dynamic, Matlab	Vehicle system
CarSim	Purchasable	AeroVironment, Inc.	Vehicle Dynamics, Animations	Chassis
COOOL	Custom	Colorado School of Mines	Object-oriented optimization library	Vehicle system
CRUISE, DRIVE, BOOST	Purchasable	AVL	Dynamic, Matlab Interface	Vehicle system
CSM HEV	Custom	Colorado School of Mines	Simulink	Vehicle system
Dymola	Purchasable	Dassault Systems	Modelica, object oriented, non-causal	Vehicle system
EPA MOVES	Open Source	Environmental Protection Agency (EPA)	Java, MySQL	Emissions
FASTSim	Open Source	National Renewable Energy Laboratory (NREL)	Excel, lumped parameter	Vehicle system
HEVsim	Custom	Wayne State University	Backwards-facing, iterative, LabVIEW	Vehicle system
HEVSIM	Custom	Wuhan University of Technology	Simulink, Forward facing	Vehicle system
HEV V-Elph	Custom	Texas A & M University	Simulink, Dynamic	Vehicle system
HVEC	Custom	Lawrence Livermore National Laboratory	EV and Series Hybrids	Vehicle system
LabVIEW	Purchasable	National Instruments	Dynamic ODE solver	Open
LFM	Custom	Electric Power Research Institute	Simulink, developed vehicle library	Vehicle system
Matlab/Simulink	Purchasable	Mathworks	Causal, Dynamic or fixed step	Open
Modelica	Open Source	The Modelica Association	Non-causal, dynamic PDE, object oriented	Open
PAMVEC	Custom	Dr. A. Simpson	Excel, Lumped parameter	Vehicle system
Powell	Custom	B. K. Powell, Ford Motor Company	Quasi-static custom model	Vehicle system
PSAT	Purchasable	Argonne National Laboratory (ANL)	Simulink GUI, Forward Facing	Vehicle system
SIMPLEV	Custom	Idaho National Laboratory (INL)	Simulink, Static Maps	Vehicle system
Virtual Test Bed	Custom	University of South Carolina	Highly dynamic computation	Vehicle system

Each of the identified modeling and simulation tools has their own advantages and disadvantages. Researchers are encouraged to take into consideration the requirements of their studies before selecting a commercially available tool or building their own from the ground up. The following section will highlight some of the characteristics of these tools and discuss considerations researchers should take into account when evaluating and selecting tools for automotive energy-use studies.

5.2 Task 1.2 Characterize simulation tools based on formulation and application.

The lengthy list of tools found was developed for a range of specific energy-use simulation studies, each with different formulations and applications, as provided in Table 1 [6]. A majority of the tools utilize Mathworks Matlab/Simulink as a computational base and are capable of simulating a variety of vehicle systems including powerplants, drivers, energy management, and controls. Varying levels of computed dynamics are available such as static lumped parameter, backward facing, hybrid forward/backward facing, forward facing, quasi-static, etc. Highly dynamic simulations often have a high computation burden but can provide high fidelity. In contrast, static simulations typically require less computation but also provide lower fidelity.

Extensibility, flexibility, and modifiability exist in different degrees depending on the simulation tool. For example, tools developed using the Modelica standard modeling language (SML) are designed to be object oriented (OO); contributing to ease of modification, extension, and flexibility through system model blocks. Simulation with Simulink tools can use libraries of standard models to provide ease of extensibility, but may sometimes have limited modifiability with proprietary blocks. Some of the purchasable tools such as Autonomie have additional limitations for flexibility based on the included models.

A few of the primary capabilities that are identified as important inclusions in the model and simulation tool selection is suggested as follows. One of the first requirements is identifying the desired question that a modeling and simulation study aims to answer. After the general structure of requirements has been developed for the study, the list of potential tools can be reduced. For example, if investigations of steady-state ideal energy consumption are the only interest, simple static models may be sufficient. As another example, if a researcher wishes to determine the electrical interactions between a high voltage bus and a fuel cell system, then more detailed models and simulation tools will be necessary. For modern systems engineering processes, including automotive design, simulation is commonly coupled with design iteration or optimization. To achieve this process effectively, model tools must have modifiable and scalable components that can be updated throughout the optimization to represent different vehicle designs. Concept of operation (CONOP) must be supplied for simulation, in many cases of automotive design this requires the development of representative drive cycles. Therefore modeling tools must be capable of having the simulated vehicle follow some defined profile as accurately as possible to fulfill the testing requirements. This list of necessities helps to form the general structure of these simulations by requirement.

There is a specification paradox when the subject of simulation accuracy is considered. The more accurate a simulation is, the more likely it is to be complex and costly in terms of computational effort. A feasible amount of time that should be allocated to running simulation has not been defined. This consideration must be evaluated in conjunction with the amount of time required to create and simulate models with sufficient detail. There is another concept of detailed design that must be considered which is the relation of model complexity to output accuracy. In many modeling efforts, there exists an informational plateau will be reached in such a way that additional modeling detail will add very little accuracy.

The modeling language that has been chosen for use in this research is Modelica [100]. The Modelica language is a free, open source language that is constantly developed and improved through OpenModelica [101]. As a forward dynamic tool, defined by vehicle control that occurs in a real-world stimulus-response manner, Modelica includes a solver developed to accurately and quickly solve Differential Algebraic Equations (DAE's). Automotive models are comprised of DAE's, making the OpenModelica modeling package a good fit for the automotive modeling and simulation [89]. Additionally, Modelica is organized as an object oriented language that allows for class definition of components and systems that can be replicated, implemented, and modified readily.

5.3 Task 1.3 Use results of Task 1.1 and 1.2 to determine a comprehensive application-specific set of requirements for vehicle simulation tools.

Based on the diversity of available simulation tools, applications, and formulations; the requirements of the simulation tools is foreseeably diverse as well. Some of the soft requirements of vehicle energy-use simulation tools match general requirements for systems engineering tools including flexibility, extensibility, robustness, validated, modifiable, and provides utility. To better understand the requirements of these tools, vehicle energy-use simulations have been performed using them [2, 3, 6, 9]. Additionally, a custom vehicle simulation tool was developed by the author, validated, and has been applied to multiple published energy-use simulation studies. A comparison of dynamic simulation of a battery electric vehicle (BEV) shown in Figure 3 between the author's custom tool and EPRI's LFM simulation tool.

Although Figure 3 only shows one comparison used for validated the developed simulation tool, many have been performed. Multiple levels of validation have been performed;

beginning at the subsystem-level (ICE, ESS, MG, etc.) and working up to subsystem interactions (ICE and generator, etc.) and complete vehicle architectures (BEV, CV, PHV, FCV, etc.). Based on knowledge gained through the previous investigations, the simulation tool developed for this research retains the required level of detail for energy-use simulation studies while requiring minimal computational cost. The models and simulations have also been developed to allow for ease of flexibility and extensibility to represent a wide range of vehicles and architectures.

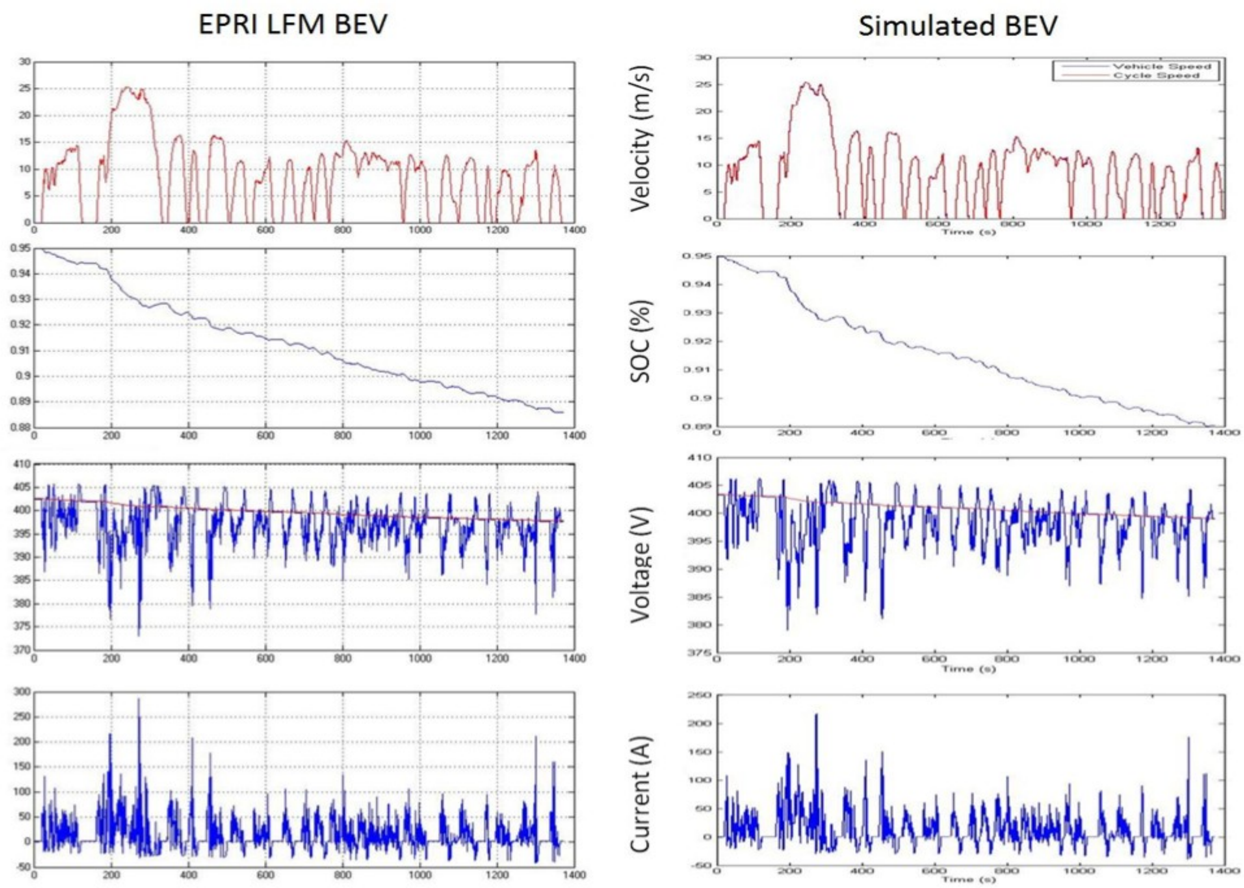

Figure 3 Comparison of simulated vehicle operation using EPRI's LFM and the author's custom models for a BEV.

From the development and use of vehicle simulation tools, and in conjunction with vehicle studies, requirements of vehicle simulation tools were developed. For vehicle energy-use studies relevant to the system design processes, it is important for vehicle energy-use simulation tools to be able to represent accurately multiple levels of the vehicle from component, to subsystem, and system. It is also desirable for the tools to include system of system considerations such as interactions the vehicle has with its environment, markets, operators, and policy.

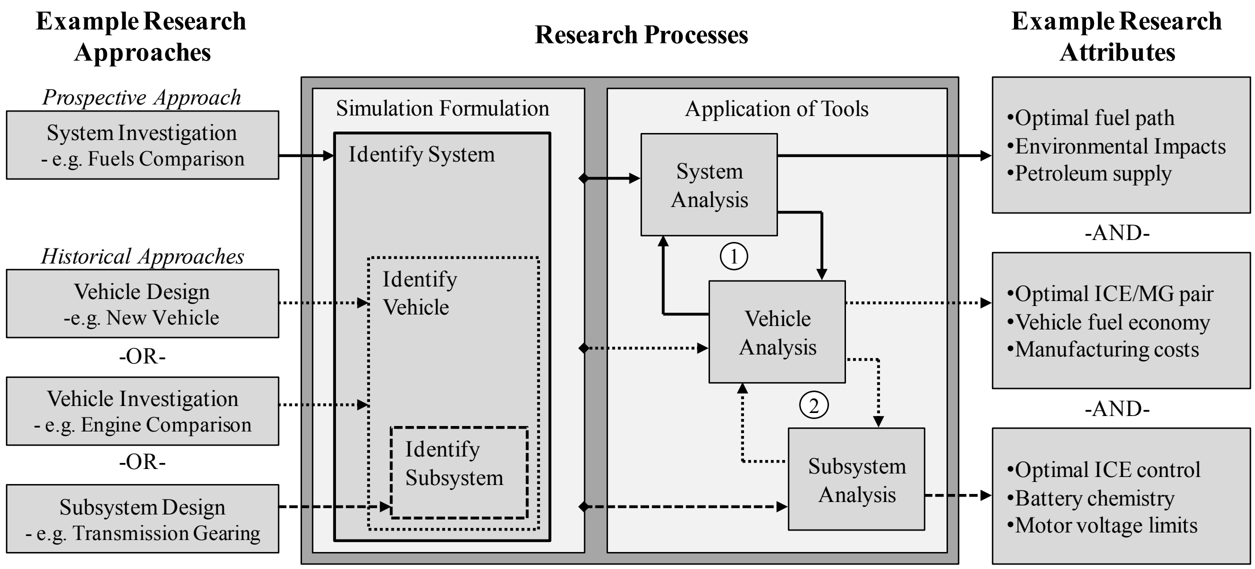

Figure 4 Representation of vehicle energy-use simulation levels.

Figure 4 provides a graphical representation of how different levels of the vehicle simulation interact as approaches are translated into associated attributes. Historically, research begins at the vehicle or subsystem level and attempts to apply simulation and analysis tools to derive conclusions (research attributes) at the system level.

The primary groups who have documented a vehicle design process with subsystem-level design objectives are PHEV conversion companies. These companies have the design objective of using their particular battery chemistry or battery system design. Because these PHEVs are conversions, the designers have no control over the other systems of the PHEV. Battery systems are often shared between PHEV platforms regardless of the effect on vehicle level performance attributes. Ronning [139] treads the line between component-level and vehicle-level design objectives by proposing engine size minimization as a design objective, subject to vehicle-level constraints on performance including acceleration times. In Figure 4, this type of study begins at the 'Subsystem Design' and subsystem-level considerations and incorrectly feeds upward to Vehicle Analysis and vehicle-level conclusions.

PHEV design processes with vehicle-level design objectives have been proposed by a number of researchers. Wong et al. [114] proposed that minimization of cost and maximization of all-electric vehicle range should be dual vehicle-level design objectives. Balch et al. [140] seeks to maximize all-electric vehicle range subject to vehicle cost and vehicle performance constraints. The design process used in [115] seeks to achieve certain all-electric vehicle ranges subject to performance constraints. In Figure 4, this type of study begins at the vehicle-level and correctly used vehicle-level analysis and vehicle-level conclusions.

PHEV design objectives that are posed at the system-level are less common. An et al. [105] proposes a design process with objectives of compliance with California Zero Emission Vehicle (ZEV) regulations. Meyr et al. [141] propose a design objective of net GHG reductions. Both of these studies begin with system-level approaches, shown in Figure 4, but the extent to which they are able to provide system-level and lower models and analysis is unclear.

Overall, a majority of published vehicle design studies have design objectives that are posed at the vehicle-level and below. On the basis of this review of design objectives from the literature it becomes evident that only through integrating component design, vehicle design, and systems design can systems-level design objectives be posed. Expressing design objectives at the system-level is necessary to achieve the beneficial system-level vehicle attributes that have been proposed for advanced vehicles. To date, the systems-level vehicle characteristics that have been attributed to advanced vehicles are not the result of a direct design process, they are byproducts of a vehicle-level design process. In order to be able to improve the systems-level attributes of vehicles we must understand the connections between the vehicle design processes at the three proposed levels.

In this research, we propose that to perform system-level research requires the development of tools that can perform modeling at the system level. Figure 4 also shows that information can only flow from higher-level sources downward and back up (loop identifiers 1 and 2). From this, system-level research can contribute to vehicle-level analysis {1} and then to subsystem analysis {2}. Higher levels of approach and formulation inherently contain information about lower levels, allowing for analysis at each sub-level. Research on a vehicle level can contribute to subsystem-level analysis {2}, but cannot appropriately be expanded to the system level without a new system-level approach.

It is important for researchers to consider the energy-use simulation study hierarchy and how it applies to their research and studies. Without correct identification of the requirements, methods, and results that are desired, incorrect tools may be applied; resulting in either incorrect or insufficient conclusions. Using this understanding of automotive energy-use simulation studies, the author has developed an extensive set of vehicle models for use in studies and the remainder of this dissertation.

5.4 Discussion of Research Question 1

What are the characteristics of tools for vehicle energy-use simulation?

Tools used for energy-use simulation of vehicle need to be available to researchers, understood, and have objectives and formulation that meet the requirements of desired investigation. The available public and private simulation tools have different formulations design specifically to certain applications. It is up to the researcher to ensure that they have selected the correct tool ultimately. As computational capabilities continue to increase, possibility exists to follow a few pathways:

1. Decrease the time required to perform vehicle energy-use simulation
2. Increase the depth (details) of vehicle energy-use simulations
3. Increase the breadth (range of considerations) of vehicle energy-use simulation

A combination of these pathways is also possible, the extent of the combined effect being limited by the allowable time and effort applied to the tools and studies and the extent of the increase in computation capability. Ideal vehicle energy-use simulation would incorporate all capabilities explored through the tasks in research question 1 including fast simulation, highly detailed, large breadth of considerations, easy to use, verified, robust, dynamic, extensible, flexible, and modifiable to meet research objectives. The importance of each of these characteristics for different studies will be investigated further in research question 2.

The tasks completed for research question 1 provide a foundation for understanding the simulation tools and the studies that can be performed for automotive energy-use. Research question 2 and its associated tasks will build on this foundation of tools to understand the best manner for applying the simulation tools and analyzing results.

6 Tools for Advancing Automotive Energy-Use Simulation Studies (RQ2)

Simulations tools have proven potential to reduce the effort required to perform automotive research through applying systems engineering principles. In applying scientific methods to automotive energy-use simulation, it is insufficient for researchers to only have an understanding of the modeling and simulation tools available, such as those presented in research question 1. In order to effectively apply these tools to automotive energy-use simulation studies the simulation tools must also be paired with effective analysis tools. Specifically, the analysis tools under investigation in this dissertation are: 1) optimization algorithms, 2) quantifying uncertainty, 3) drive cycles as CONOP, and 4) fleet-level analysis. Although many other analysis tools are potentially available for application to automotive research, these tools have been selected for their potential to simultaneously reduce the total effort required to complete a study while increasing the validity and robustness of the results and conclusions.

The following sections will provide detailed investigations of the four analysis tools proposed. Each of the tools will be applied to state-of-the-art automotive energy-use simulations through individual studies. The methods, results, and conclusions will be provided for each analysis tool such that future researchers can apply them to their own studies. The conclusions of these sections will also provide recommendations. Each of the analysis tools explored in the following section provides significant benefit to automotive energy-use simulation studies when applied appropriately.

6.1 Task 2.1 Determine which Algorithms are Efficient and Robust for Vehicle Simulation Optimization

Optimization as a technique is very general in its use of achieving a most desirable solution defined within the parameters of the algorithm. Within the umbrella of optimization there are many individual techniques and caveats that must be understood to improve the optimality of the optimization. One reason is that different algorithms search for different trends within data and have different techniques for finding solutions. Also, there are parameter values that define the operating conditions of each of the algorithms differently and affect their performance. The principles behind this dilemma are what lead systems engineers working with optimizations to examine multiple optimization algorithms to understand both the techniques and goals of each [110].

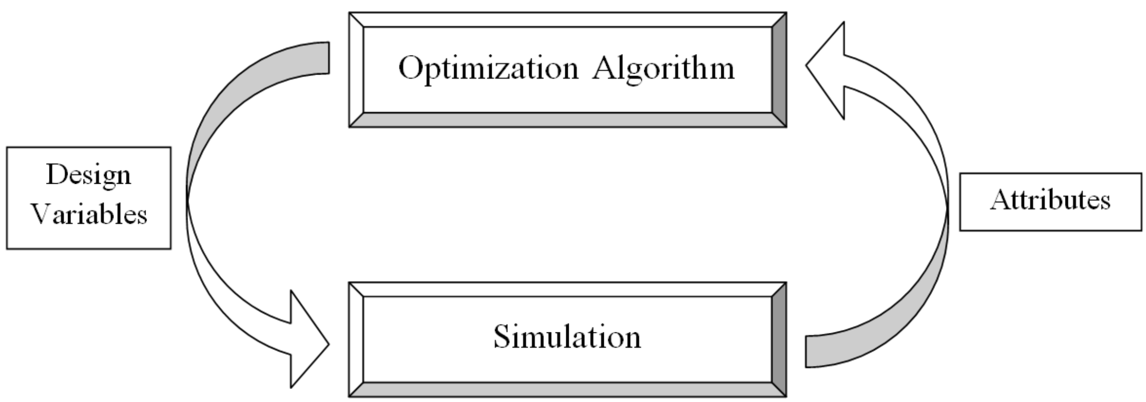

Figure 5 Optimization process feedback loop

In the case of complex data sets, one optimization method may result in a solution that is optimal within its analyzed area, by definition a local maxima or minima. Another algorithm may find a completely different solution. If these optimizations find different solutions their overall utility will be different between one another. It is also possible that both algorithms find different solutions that achieve exactly the same result, e.g. the same cost and performance in a sample vehicle optimization. If two solutions are different but result in the same thing, how does a designer know which is the best? The answer can only be obtained through further consideration of the objectives of the design. For example, any components from one design may be more difficult to obtain than another. Validation testing performed in this study presents an example of multiple optimums in the following section Validation of Optimization Algorithms where some of the optimizations converge to similar costs but with different design decisions. The solutions found in each case were optimal within their respective effort. Through the utilization of multiple algorithms we can have a better understanding of what the possible optimum solutions are, and a better understanding of the overall design space.

A consideration when choosing optimization algorithms is the behavior of the simulation and design space being used. As was presented, there are chances for a design with multiple solutions. For example, imagine a mountain range with multiple peaks of the same height and we are trying to find the highest point in the region. Some design objectives may result in a single optimal solution. While a technique that simply observes the slope of the land may find a single peak quicker, a technique that takes random sampling over the whole area may find a better solution, albeit slower. These differentiations in technique describe some of the underlying principles in the many optimization techniques where the slope of the mountain may relate more directly to the slope of a cost function peaking at an optimal value. Many other options such as discontinuities, "flat" areas in objective functions, and seemingly random distributions cause complexities in optimizations and increase the need for both an understanding of the design space and the different algorithms that should be utilized. The algorithms used within this study that will be explored in the following sections including Divided Rectangles (DIRECT), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated

Annealing (SA) [83, 123]. Between these algorithms different methods of optimization are used. All of the methods explored are global optimizers with derivative-free algorithms (no gradient or slope as the previous example mentioned). Global searches refer to an ability to evaluate design variables throughout the design space. Due to specified design criteria, global searches may or may not be limited to specified design spaces, in which case the global search can occur at any point within the design space. All of the algorithms used are heuristic, meaning they incorporate methods that "learn" and make increasingly improved design decisions as the optimization search progresses. The DIRECT optimization algorithm uses a deterministic method that is mathematically consistent whereas SA, GA and PSO all use stochastic methods. Stochastic algorithms incorporate random search methods whereas deterministic algorithms are structured. Further explanation of the differences and unique methods of optimization for each of the algorithms is included in the following sections.

6.1.1 Optimization Algorithm Methods

6.1.1.1 Divided Rectangles

The Divided Rectangles (DIRECT) optimization algorithm is a global search method that is deterministic and capable of considering design points on both a local and global scale [111]. The DIRECT method, developed by Donald Jones, is a modification to the Lipschitizian method which eliminates the need to provide a Lipschitz constant, a weighting factor to determine emphasis on local versus global searching. Being a deterministic global algorithm, the DIRECT algorithm uses previously evaluated functions to determine future search directions relative to design criteria [83, 123].

The DIRECT method starts an optimization search by first creating an n-dimensional unit hypercube, where n is equal to the number of design variables. The first function evaluation is performed at the center of the initial hypercube and then the cube is trisected to form three hyperrectangles. A function evaluation is performed on the resulting two hyperrectangles (the third having been performed in the first step) and the lowest cost function is identified for continuation (when minimization is specified). The hyperrectangle with the lowest function value is then trisected and the center points of the resulting hyperrectangles evaluated. This process is continued for each iteration in so that the lowest evaluated hyperrectangle is divided to narrow in on the optimum point. The trisecting and dividing of hyperrectangles is performed a number of times during each iteration equal to the number of different sizes of hyperrectangles. This is allowed by using all of the values of the Lipschitz constant. Thus it is insured that the optimization is performed along both global and local paths. A visual representation of the first three iterations the DIRECT algorithm optimization process for a two dimensional problem (n = 2) is shown in Figure 6. As can be seen in the second iteration of Figure 6, two sizes of hyperrectangles are present and therefore eligible to be trisected further. In the third iteration there are now three sizes of hyperrectangle that will be trisected, each chosen by their function value relative to other hyperrectangles of the same size. The process continues until a maximum number of function evaluations or some other criteria such as achieving a desired minimum is achieved.

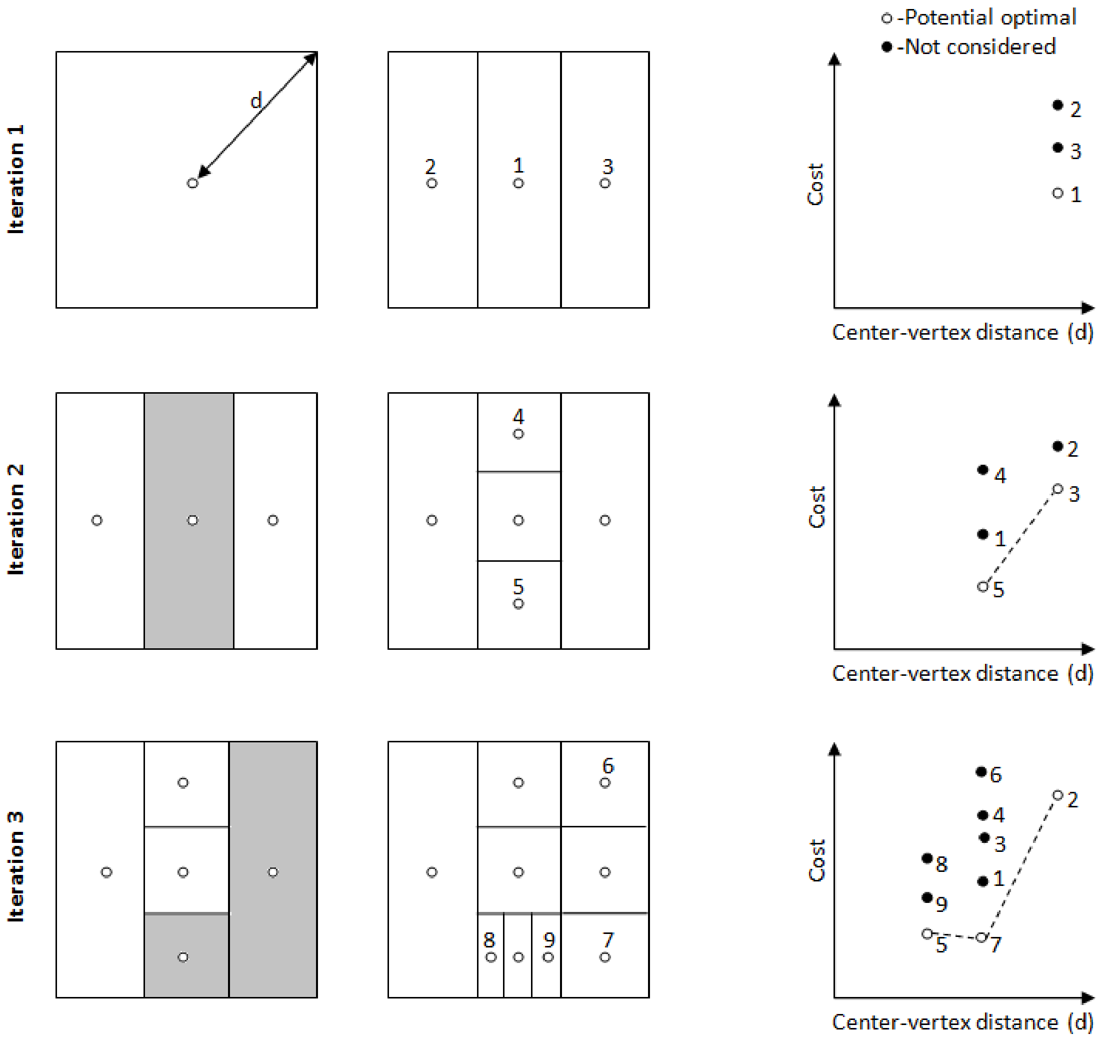

Figure 6 Graphical representation of the first three iterations of the DIRECT algorithm.

In Figure 6, the optimal hyperrectangles selected to be trisected during iteration have been darkened. The DIRECT algorithm chooses different sized rectangles to achieve both a local and global search. Optimal hyperrectangles are chosen by having the lowest function value for their size as is shown in Figure 6. In Figure 6, the horizontal-axis represents the distance from the center to the vertex of each hyperrectangle and the vertical-axis represents objective function value at the center point of the corresponding hyperrectangle.

6.1.1.2 Genetic Algorithm

The Genetic Algorithm (GA) used for optimization is a stochastic global search algorithm based on Darwin's concept of natural selection [83, 123]. The algorithm behaves as an evolutionary population in which the fittest members survive and replicate and weak members are eliminated. This process applies each member of the population as a set of design parameters which are generated and the fitness of each of these members is determined by the function evaluation of those design parameters for that member. Within the algorithm several natural processes occur including mutation, drift, natural selection and crossovers between the members as new generations are created. In Equation 1 a possible combination of genetic algorithm parameters is provided where p_i^{n+1} represents the next multi-dimensional design point, p_i^n represents the previous design, p_j^n is other good designs found, p_k^n represents poor designs found with a random probability of being included, drift represents minute adjustments, and mutation allows for changes in magnitude and direction to the new design point. Design points with good function values or fitness are used to produce further design points. Design points with poor function values are excluded, allowing for the best design parameter points to be identified and used.

Equation 1

$$p_i^{n+1} = (p_i^n + p_j^n + rand_1(p_k^n) + drift)(mutation)$$

The process begins with a set of initial design parameter points, or an initial population, which is then evaluated. Based on the function values of each of the members of the population some are allowed to continue and produce additional design points (which are slightly different than the original points) while others are eliminated. Similar to iterations in other algorithms, each time a new set of design points (children) is created from previously evaluated design points (parents) a generation has occurred. A graphical representation on the GA search process is provided in Figure 7. The algorithm can be terminated based on a number of criteria including allowable number of generations, achieving a desired function value or by achieving a population which does not vary greatly over multiple generations.

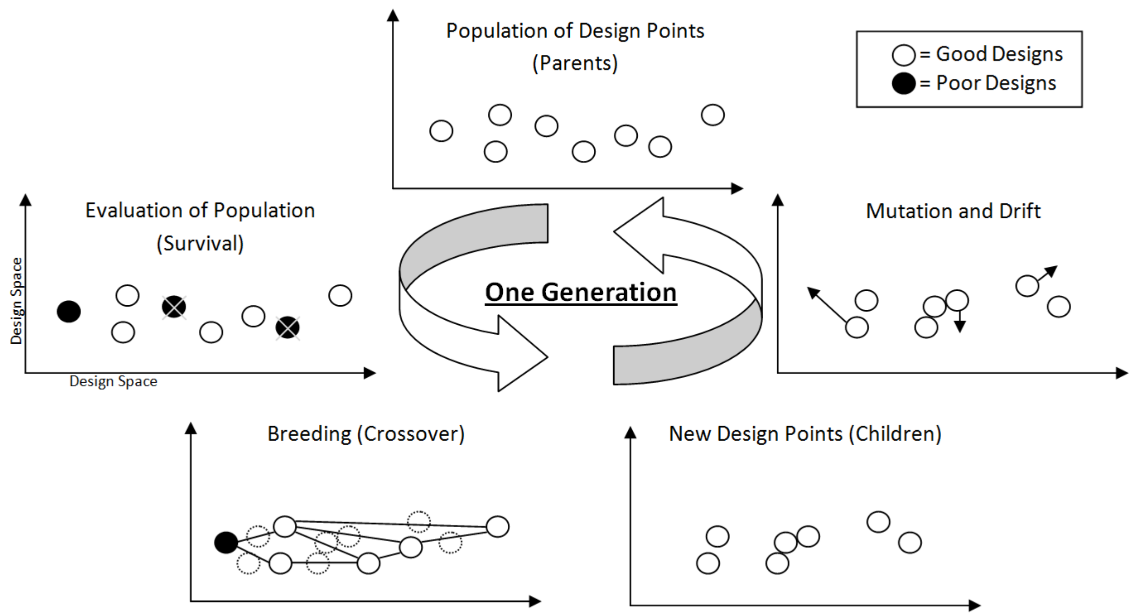

Figure 7 Genetic Algorithm search process example representation for one generation

6.1.1.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a stochastic global optimization algorithm which utilizes swarm intelligence found in natural systems such as flocking birds, schools of fish, bee colonies, or herds of animals [123]. The algorithm generates a population, or swarm, of design points which behave as a flock within the design space searching for an optimal design solution relative to the objective function. The PSO technique was developed by Kennedy and Eberhart in 1995 to mimic the natural interactions of members of a group in an effort to find a global best solution.

The PSO algorithm begins by defining a population size which will each stochastically select initial design points, also known as positions, and their objective function value will be calculated. Between each of the particles a particle specific best design is identified and saved through the optimization (*pbest*) as well as a group specific best design point (*gbest*). Although each particle is represented as being size less, each member of the swarm moves within the multidimensional design space in an effort to achieve a global best solution with movement determined by the particle's current position, best design point locations (*pbest* and *gbest*), particle velocity and particle inertia. Using an algorithm, a velocity for each member is determined to represent how movement will occur within the multidimensional design space; this is shown graphically in Figure 8 where one particle (design point) is affected by the other points and a stochastic parameter to determine a future position and velocity.

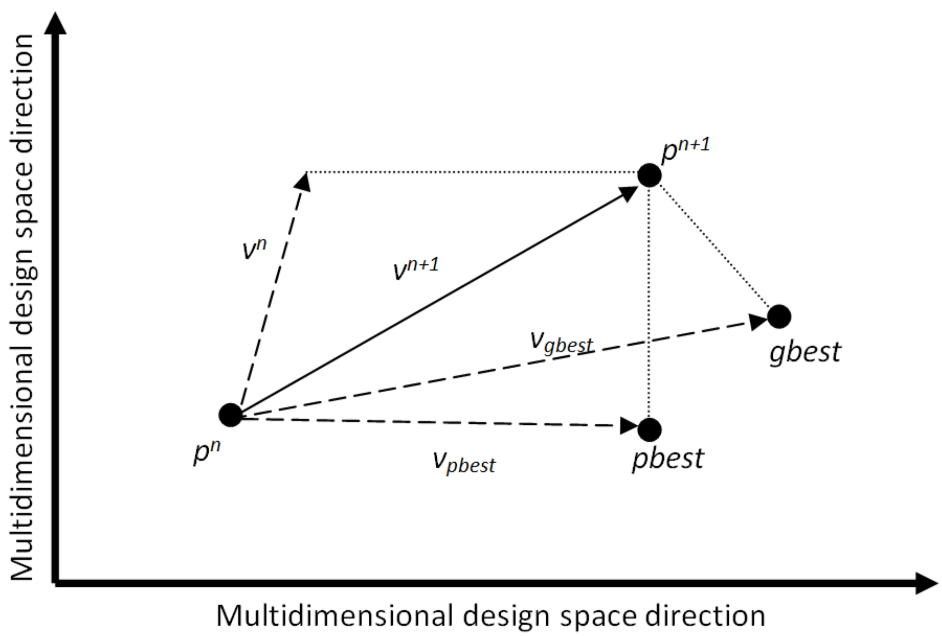

Figure 8 Graphical representation of PSO search algorithm showing contributing movement components.

As can be observed in Equation 2 and Equation 3, the velocity of each member of the swarm population is determined based on random as well as previously determined characteristics of the design space from other members of the swarm. In Equation 2, v_i^{n+1} represents the velocity of particle *i* at iteration *n+1*; α_1 and α_2 are weighting factors for the random numbers $rand_1$ and $rand_2$ between 0 and 1, *k* is a weighting function, p_i^n is the position of the particle, $pbest_i$ is the best position of particle *i*, and *gbest* is the global best position found by the swarm. Equation 3 shows the relation of how particle positions are updated during subsequent iterations.

Equation 2

$$v_i^{n+1} = kv_i^n + \alpha_1 rand_1(pbest_i - p_i^n) + \alpha_2 rand_2(gbest - p_i^n)$$

Equation 3

$$p_i^{n+1} = p_i^n + v_i^{n+1}$$

Using the technique above, PSO searches the global design space in a combined random and deterministic manner which suits nonlinear multi-objective optimizations well and is able to achieve local and occasionally global best designs.

6.1.1.4 Simulated Annealing

Simulated Annealing (SA) is a stochastic global search algorithm which is designed to follow a process similar to annealing (cooling) of metals [83, 123]. In the SA algorithm, each combination of design variables is simulated to behave as an atom within the metal (design space) being annealed. The process is similar to a Monte Carlo simulation process initially since it randomly searches the global design space. But as the system moves further along in the optimization each particle becomes more limited in its searchable area. The constriction of searchable design space is caused by a cooling of the system which is provided by a cooling schedule. The cooling continues until a minimum temperature is reached or a desired function value has been achieved. Examples of the SA optimization search method are shown in Figure 9.

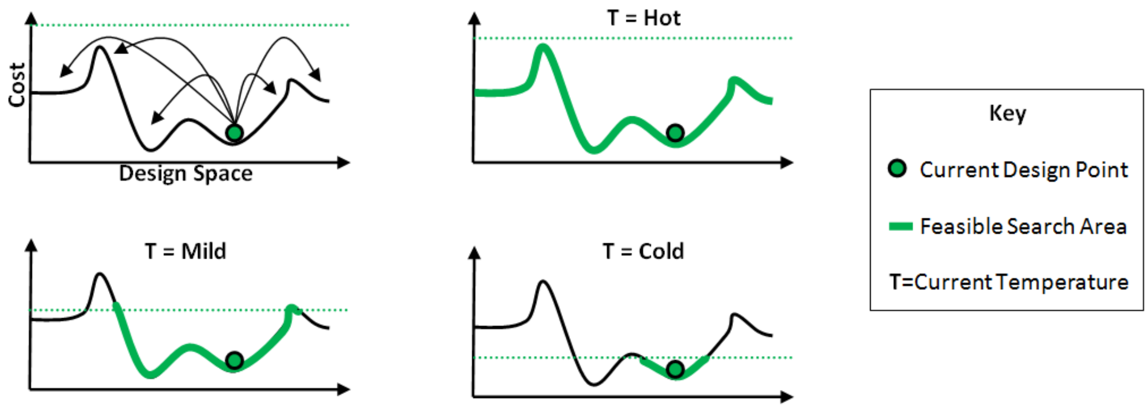

Figure 9 Schematic diagram of Simulated Annealing optimization algorithm search process.

During the initial step of a Simulated Annealing optimization process a prescribed number of atoms are identified which represent points within the design space. Each of the function values are calculated for the atoms and potentially optimal points are remembered by the algorithm. Movement of each of the atoms within the design space for continued iteration is determined by the temperature (*T*) of the system as well as random search and previously evaluated design point function values. The temperature of the system is determined by a cooling schedule which uses the number of function evaluations that have been performed as well as values of different design points. As the algorithm is meant to simulate an annealing process, each of the atoms move more freely when the system is at higher temperatures and settle into a more stable orientation as the cooling slowly occurs. Potentially optimal points that are identified by the system as they are evaluated have a higher probability of being incorporated into future search directions as the temperature decreases. The probability of a point being accepted or rejected if it is worse than a previous point is determined by the Metropolis probability P criterion given in Equation 4 where f is the evaluated objective function value and T is the current temperature.

Equation 4

$$P(f,T) = e^{\left[\frac{fnew - fcurrent}{T}\right]}$$

In this way the algorithm is freer to search more of the global design space and only becomes restricted as the algorithm nears a possible optimal design point. The importance of incorporating the temperature into the determination of search criteria is that it allows the likelihood of being stuck in a local optimal point to be reduced. The algorithm continues to search for optimum points during the cooling schedule until one of the completion criteria has been achieved including the system temperature reaches a predefined minimum, a maximum number of function evaluations have been performed, or a desired function value has been reached.

6.1.2 Validation of Optimization Algorithms

The optimization algorithms that have been selected; Simulated Annealing, Divided Rectangles, Genetic Algorithm, and Particle Swarm Optimization, must be tested to verify performance. Each of the algorithms has previously been tested by their developers to verify that they are capable of identifying local minima in a global search optimization given a sufficient number of function evaluations. Some of the tests performed included running each optimization on field standard test functions such as the "Six Hump Camel", "Rosenbrock", and "Goldstein-Price" which each contain multiple local minima, global minima, and dimensions [123].

Of primary importance for validation in this study is the performance of the optimization algorithms using vehicle simulations. Previous work performed by Gao (et al.) [123] tested the performance of each of the four algorithms selected in optimizing a six dimensional vehicle design problem during 400 function evaluations using a parallel type vehicle architecture. The design variables used in the optimizations performed by Gao included both controller specific and component specific applications which were Battery State of Charge Maximum, Battery State of Charge Minimum, ICE Power Limit, EM Power Limit, Final Drive Ratio, and Batter Number of Cells. The design space upper and lower bounds are shown in Table 2.

Table 2 Design variable allowable ranges for optimization algorithm performance comparison.

	Max SOC	Min SOC	Engine (kW)	Motor (kW)	Fd	ESS Cells
Upper	0.9	0.4	100	80	4.0	350
Lower	0.6	0.2	40	10	2.0	150

Although all of the design variables are quantitative by definition, some of the component variables may be considered to be more qualitative because they define limitations on the components (in the case of Motor and Engine power limits) instead of constant operating parameters.

6.1.3 Optimization Algorithm Performance

The results of Gao's optimization algorithm performance comparison over the 400 function evaluations allowed show that the Simulated Annealing (SA) algorithm performing the best by achieving the highest objective function value, for a maximizing optimization, with DIRECT, GA, and PSO following in respective order.

In an effort to replicate the algorithm comparison performed by Gao using PSAT, the same design variables and vehicle architecture (a parallel hybrid electric vehicle (HEV) were used to perform a multiple algorithm optimization of vehicle simulations using custom vehicle models. Although the exact specifications of the base vehicle used by Gao were not known, the same design space limitations were implemented to define lower and upper bounds for each of the design variables. Using identical base vehicles is not a crucial factor for this comparison since the goal is to compare the overall performance of each of the algorithms on a simulation based vehicular optimization. The results of the optimization algorithm performance test performed for the work done in this paper is presented in Figure 10.

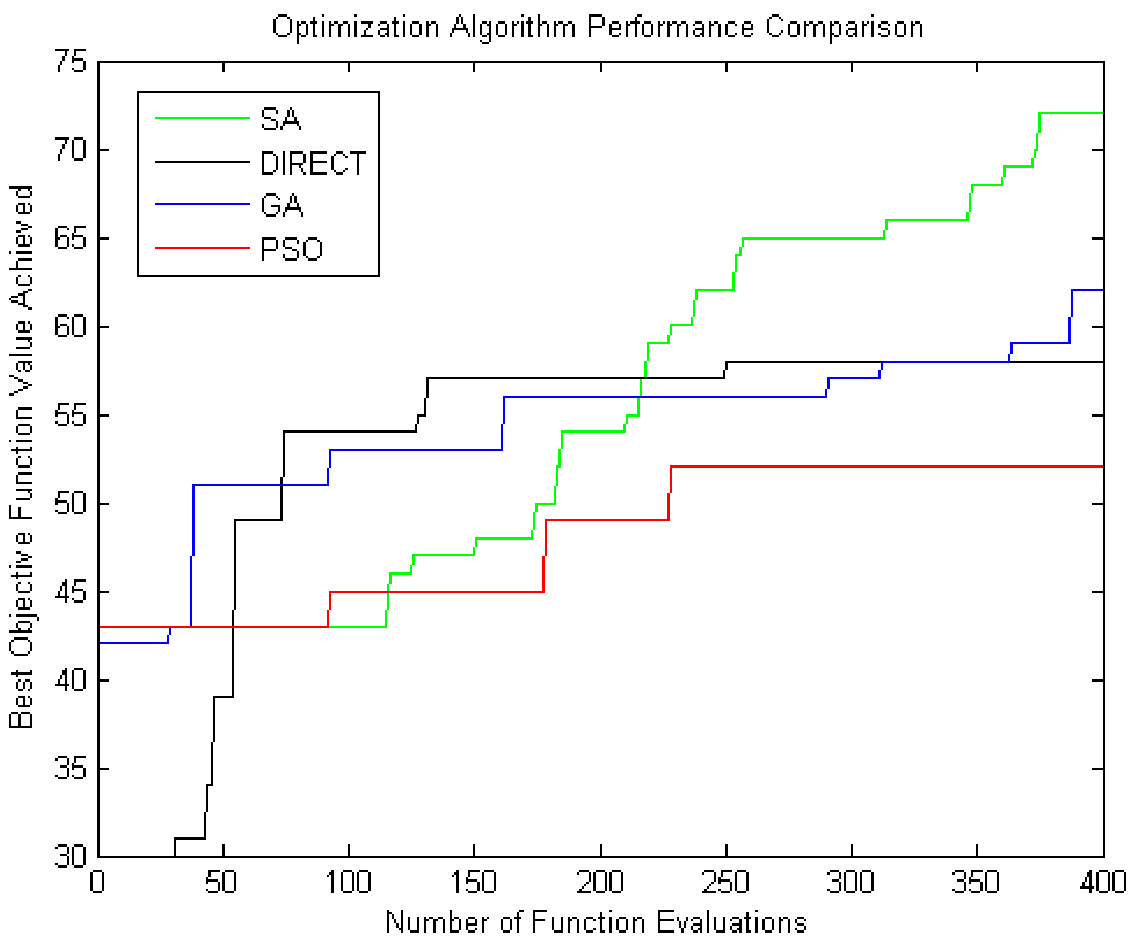

Figure 10 Comparison of optimization algorithm performance

The specific values of the objective functions are not directly comparable between the two algorithm performance test efforts due to the differences in vehicle type used, but the overall trends of each of the algorithms is meaningful. The results of a comparison between the two optimization algorithm performance tests show that in both cases the Simulated Annealing (SA) algorithm was able to achieve the highest objective function value while Particle Swarm

Optimization achieved the lowest maximum objective function value over the observed number of function evaluations. It is also observed that if the performance tests had been limited to fewer function evaluations, such as 100 iterations, the results of the comparison would have been different since the profiles of each algorithm varies. A comparison of the final decision variable selections and objective function values is provided in Table 3 and Table 4 to compare the selections made by each of the algorithms from both the previous study performed by Gao and the current study.

Table 3 Results of BMG Optimization Algorithm Performance Test

	Maximum Objective Value	Function Evaluations at Max Value	Max SOC Allowable	Min SOC Allowable	Max Engine Power (kW)	Max Motor Power (kW)	Final Drive Ratio	Number of Battery Cells
DIRECT	57.80	250	0.75	0.21	82.9	68.5	3.00	250
SA	72.20	375	0.77	0.20	85.3	79.2	2.55	215
PSO	51.79	228	0.90	0.20	71.2	71.9	3.03	286
GA	62.39	388	0.72	0.21	85.8	74.4	2.87	165

Table 4 Results of Gao's Optimization Performance Test

	Maximum Objective Value	Function Evaluations at Max Value[1]	Max SOC Allowable	Min SOC Allowable	Max Engine Power (kW)	Max Motor Power (kW)	Final Drive Ratio	Number of Battery Cells
DIRECT	39.64	310	0.84	0.25	83.1	20.2	3.90	245
SA	40.37	400	0.78	0.22	82.4	21.9	4.00	311
PSO	37.60	390	0.78	0.26	87.1	14.8	3.42	238
GA	37.10	395	0.89	0.34	95.5	24.2	3.49	300

[1] Approximate value

When considering the profiles of each of the optimizations, it is important to remember that there are many operational parameters that define the methods that each of the algorithms invoke as presented in section 6.1.1. The specific parameters used for each of the algorithms in previous work are unknown, making it difficult to create optimizations that perform in the exact same manner when comparing optimization performance. In addition to unknown algorithm parameters, the nature of each of the algorithms to implement random searching allows for additional variation between results, even when optimizations are performed under identical conditions.

6.1.4 Optimization Algorithm Consistency

When considering the validation and performance characterization of optimization algorithms it is important to test for consistency. The heuristic-stochastic methods implemented in the SA, PSO, and GA provides a chance for the algorithms to perform differently on subsequent optimizations even when identical design space, objectives, and constraints are used. Although the algorithms were initially classified based on performance in the preceding section, additional optimizations were performed using each of the algorithms on a different design simulation to observe repeated performance for consistency. The DIRECT optimization algorithm is included in the following analysis simply for basis comparison. The deterministic method implemented by DIRECT ensures that identical optimization search paths will be used on subsequent optimization runs of the same design space. Therefore, the DIRECT optimization algorithm can be considered to have 100% consistency because the same solution will always be found for a given number of function evaluations of identical simulations and design spaces.

Two primary observations are desired through the additional optimizations; the consistency of the final solutions as well as consistency of the overall optimization profile trace;

and does the algorithm perform with consistent advancement for continued iteration or simply get lucky occasionally? Together these performance metrics allow for a qualification of each algorithm's robustness to the complex design space. Because of the stochastic nature of the algorithms there is a possibility that the algorithms may begin their search in a highly desired area, but also the possibility that they may begin in an undesirable design. The examples where the algorithms begin in the poor design areas are of much more interest for performance comparisons. If the algorithm can consistently identify more desirable designs when starting in a poor design area, it is more likely to achieve good designs in future efforts. In contrast, an optimization that begins its search in a desirable design area, although it started there randomly, cannot be evaluated effectively for performance. This consideration is made since each of the stochastic methods has equal probability of starting in the more desirable design locations if they use the same random number distributions. The performance evaluations are based on the learning and advancement ability of the algorithms rather than initial design decisions.

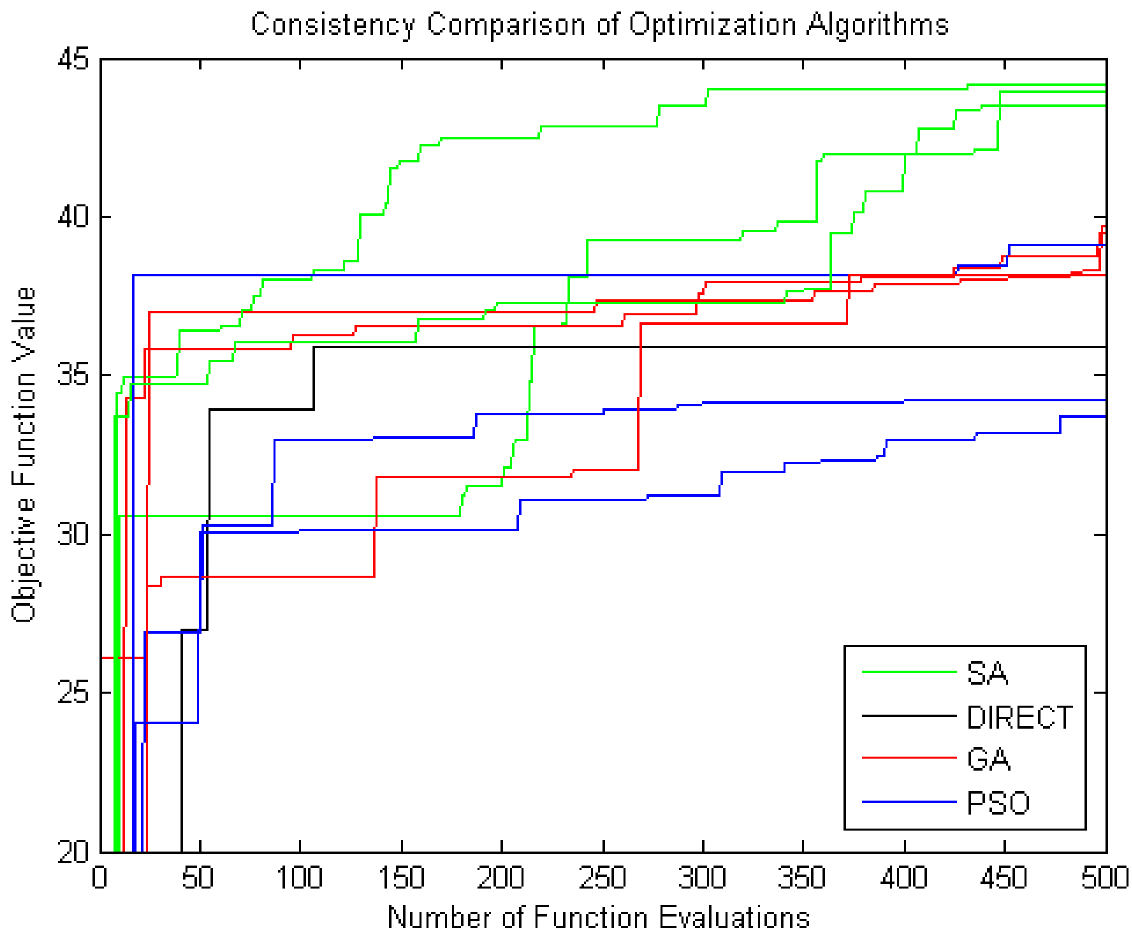

Figure 11 Consistency of optimization algorithms for the same design space

To achieve a usable representation of each algorithms consistency and performance, three identical optimization runs were performed on identical vehicle simulations. The results of these runs are contained in Figure 11. Observing the results of the consistency comparison shows that the Simulated Annealing and Genetic algorithms perform well and final designs have similar cost values across the same algorithms. This performance is desirable especially when combined with different design paths taken for the three optimizations for each algorithm, each with varying speeds at which they approach the identified optimum. As was discussed previously, even though the Particle Swarm Optimization has one instance that achieves a higher objective value than the other two, it can be seen that this design was located early in the search and may be attributed to the random search methods. In general the PSO algorithm performs poorly on the sample design problem.

The validation of the optimization algorithms show that the Simulated Annealing algorithm performs the best both in terms of objective function value achieved and consistency. The Genetic Algorithm performs the second best with similar consistency but lower objective values identified. Divided Rectangles shows perfect consistency but achieves the second lowest final objective function value over the number of function evaluations observed. The Particle Swarm Optimization performs the poorest over the design space and function evaluations used in the validation. Simulated Annealing will be used in the following sections because of its performance and consistency during the validation.

6.1.5 Results and Discussion

As an exploratory demonstration effort into direct comparison of hybrid vehicles through simulation optimization four vehicle architecture types (series, parallel and power split HEVs and a CV) have been optimized independently. To perform this optimization, identical SA algorithms and cost functions were implemented in the optimizations of each architecture type. The SA algorithm was selected for this study based on previous observations of its performance in a similar design space. Each of the vehicles feasible design space constraints included performance criteria such as zero to sixty mile per hour time, zero to eighty mile per hour time, forty to sixty mile per hour time, and maximum acceleration achieved. The values of the performance criteria are provided in Table 5.

Table 5 Performance Requirements used in sample optimization comparison.

0-60mph	0-80mph	40-60mph	Max Acceleration
≤ 14sec	≤ 22sec	≤ 5sec	≥ 2.0 m/sec2

The ability for the simulated vehicle design to achieve the above criteria was combined with the additional cost function components. The combined cost function included a summation of vehicle component costs as well as fuel costs incurred over a five year period based on the fuel economy calculated from each simulation. Vehicle glider costs are considered constant and not incorporated into total cost. The five year time frame was chosen to represent a common single ownership period, although the simulation could easily be modified to represent any time frame. Each of the simulations was allowed to converge when the cost failed to improve more than $50 over 100 iterations and only if the SA algorithm temperature was below a certain level. Although additional iterations may show improved solutions, the information available at the chosen convergence is sufficient to make preliminary analysis of the data to show the utility of using the methods outlined in this work. Definitive optimization efforts for specific vehicle types and constraints may wish to increase the convergence criteria to allow for more possible iterations.

6.1.6 Design Space Analysis

One of the advantages of performing optimizations of the selected vehicles is increasing the amount of information about the designs within the provided design space. By performing many simulations, with global optimization efforts covering a wide range of designs within the design space, interpretive mappings of the design space can be made. With these maps it is possible to identify specific regions of the design space which may be desirable or undesirable relative to the defined objectives. Additionally, preliminary observations of the design space mappings allow for quasi-validation of the necessity for utilization of the heuristic-stochastic optimization algorithm as opposed to other algorithms such as gradient based or statistical optimizers. Observations of nonlinearities, multiple minima and maxima, as well as an integration of the objective function as it is defined allow for a classification of the design space.

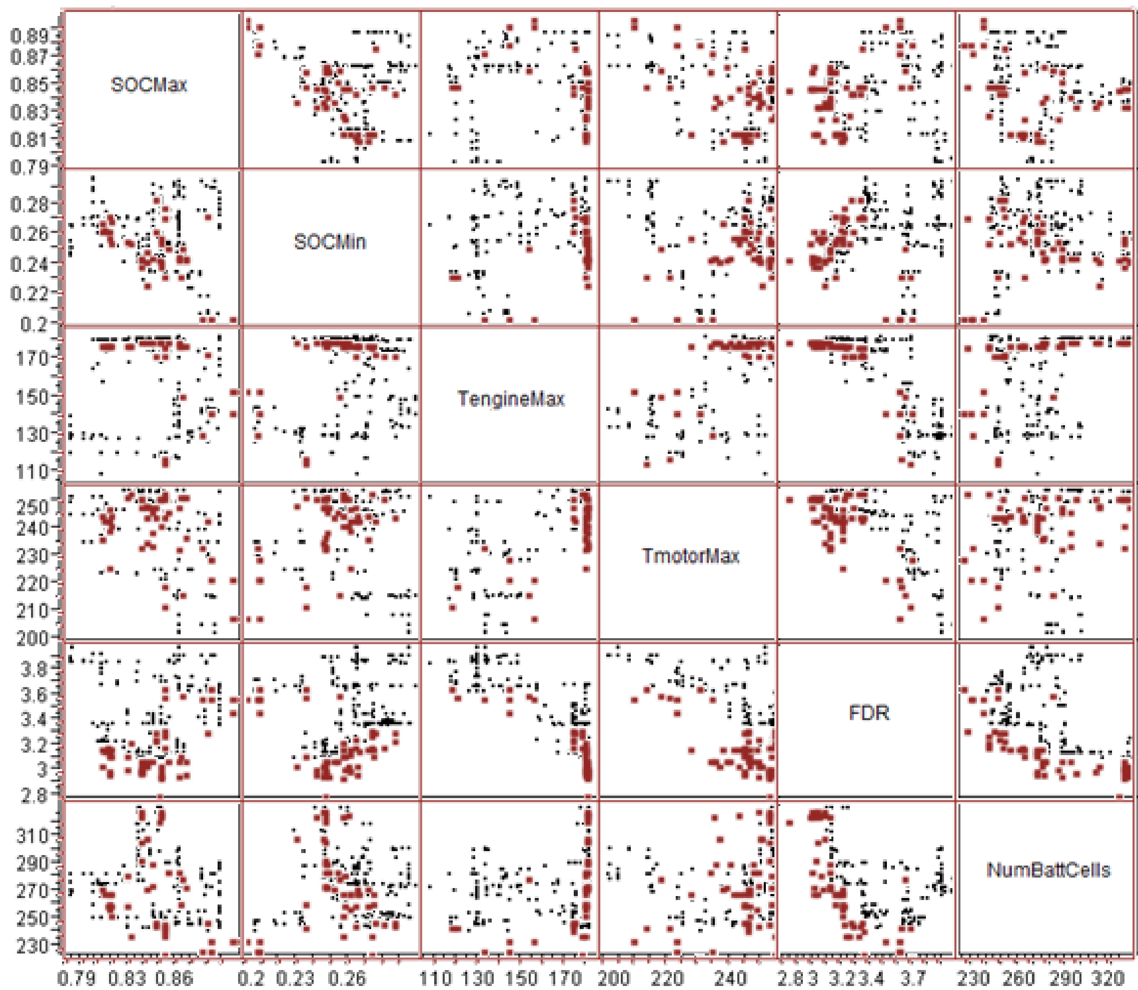

Figure 12 Scatterplot matrix of feasible (black) and infeasible (red) designs for a parallel vehicle optimization

The first step taken for analysis of the design space is to observe the regions of the design space searched by the optimization algorithm as well as identifying feasible and infeasible design regions within the designs space that affect the algorithm's search paths. Scatter plots of the observed design variables through the optimization for feasible and infeasible designs as defined by the performance constraints are provided in Figure 12. The design points provided in this comparison show that the infeasible regions are located throughout the design space instead of being restricted to limited regions for most of the design variables. This scattering of infeasible designs throughout causes additionally complexity in the design space as there is a decreased probability of accurately being able to locate feasible designs solely based on previously evaluated design points.

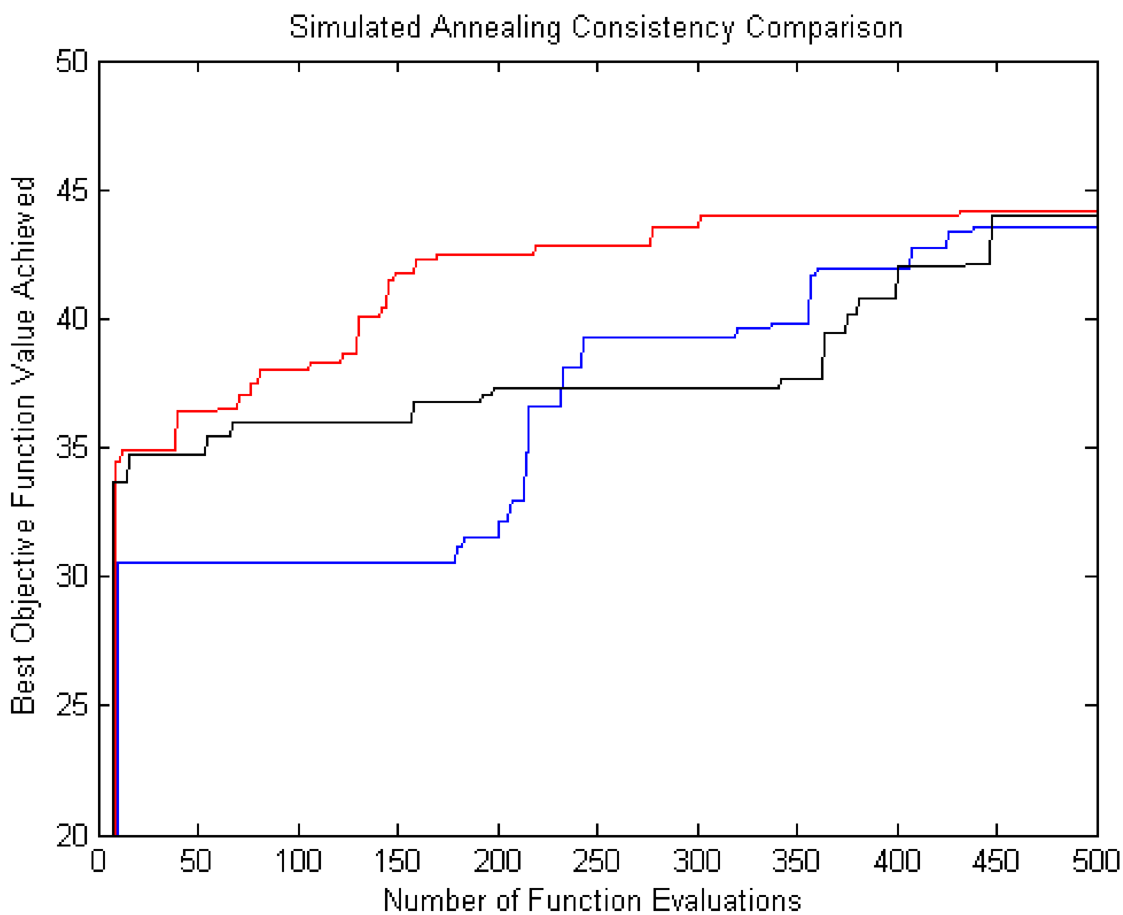

Figure 13 Consistency comparison for three Simulated Annealing optimizations

By extending the analysis of the design space to include the two other SA optimizations performed for the consistency comparison provided in section Optimization Algorithm Consistency, we can observe the regions that each optimization searched. As mentioned previously, all three of the algorithms achieved similar final objective function values as is shown in Figure 13. Additionally, since the SA optimization shown in red in both Figure 13 and

Figure 14 achieved more desirable objective function values early in the search, it limited its search areas to those that exceeded its already found designs. In comparison the other two SA optimizations shown in black and blue in Figure 13 and Figure 14 search much broader ranges of the design space before converging. It should be noted that in Figure 14 many of the designs selected by the SA optimization indicated with black markers are covered by similar designs selected by the SA optimization indicated with blue markers.

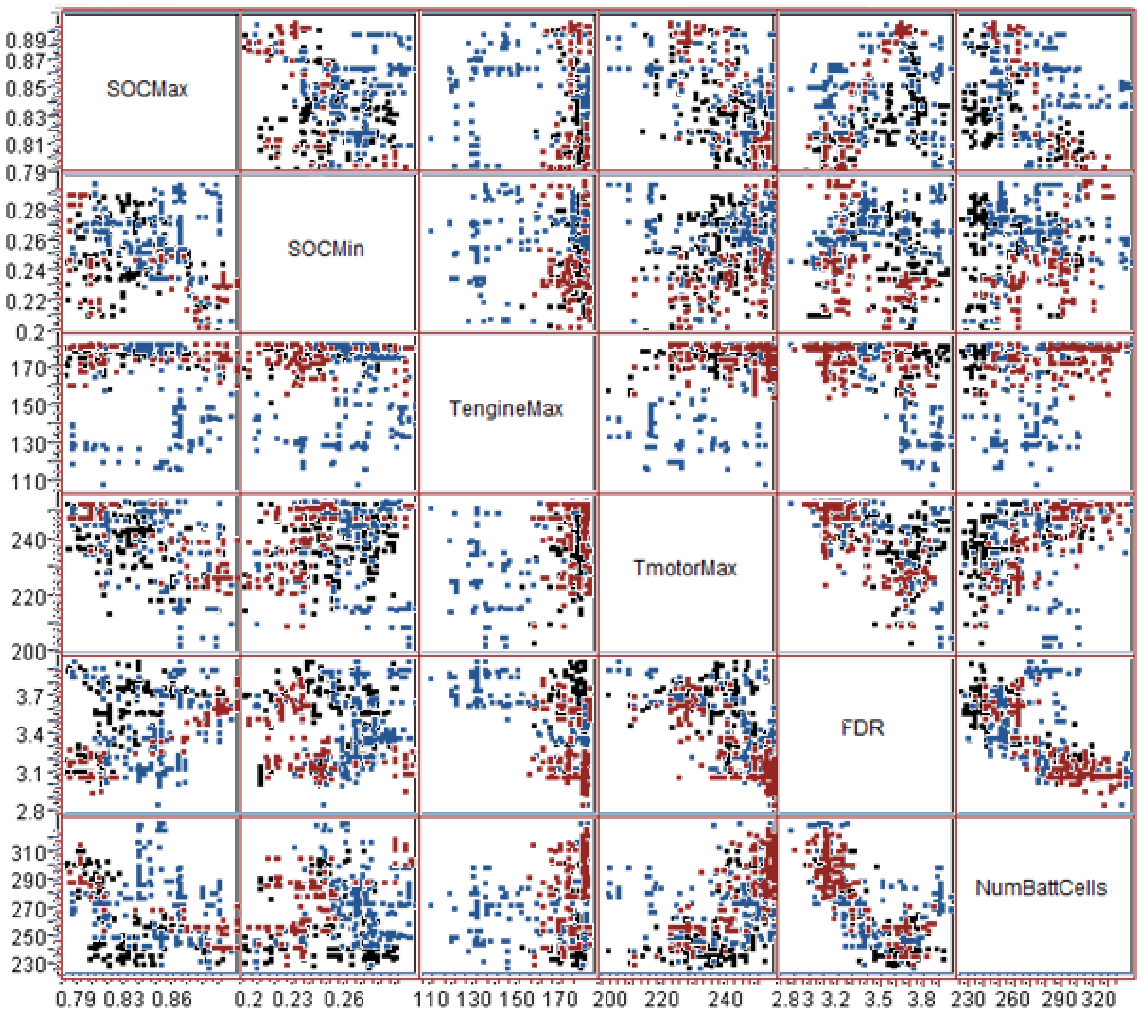

Figure 14 Design space search areas for Simulated Annealing optimization consistency comparison with colors representing different optimization runs.

By applying a Neural Network model to the output data from the optimization of the parallel vehicle architecture discussed in the past design space analysis examples we can create a relatively accurate (R^2=0.93) depiction of the effects of different design variable combinations on the objective function value. Two examples of "slices" of this design space mapping are provided in Figure 15 and Figure 16 which compare Number of Battery Cells vs. Final Drive Ratio vs. Cost and Engine Max Torque vs. Motor Max Torque vs. Cost, respectively. It can be identified graphically in these figures that there exist multiple contours contributing to multiple local minima and local maxima for some variable combinations and relatively smooth design spaces for other variable combinations.

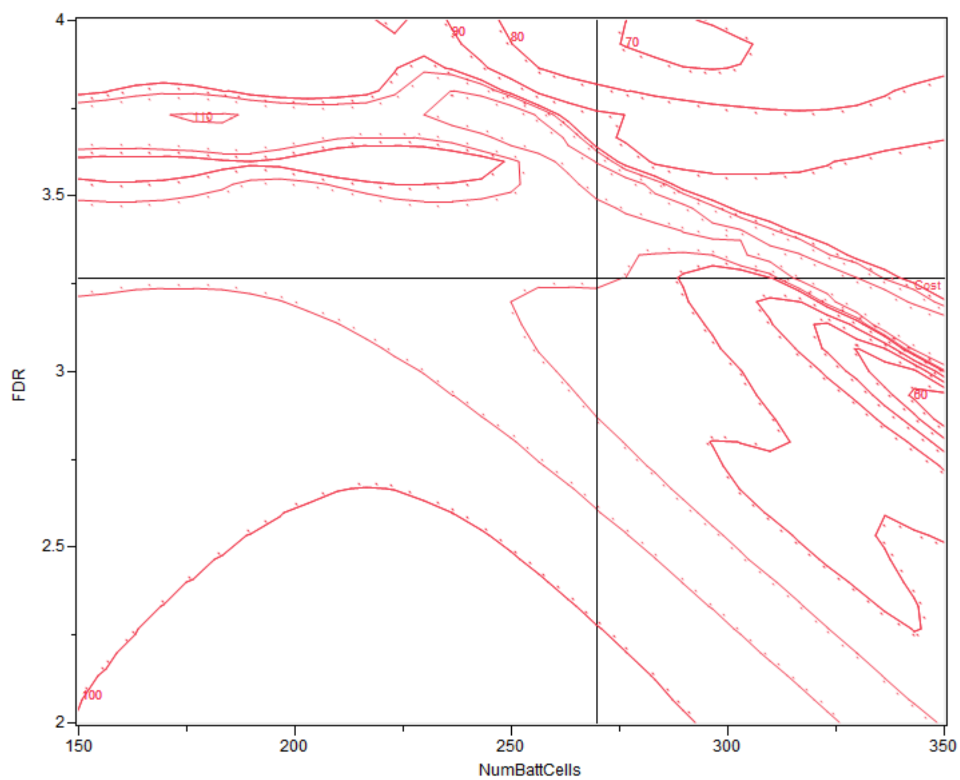

Figure 15 Contour selection of the parallel architecture design space for Number of Battery Cells vs. Final Drive Ratio vs. Cost

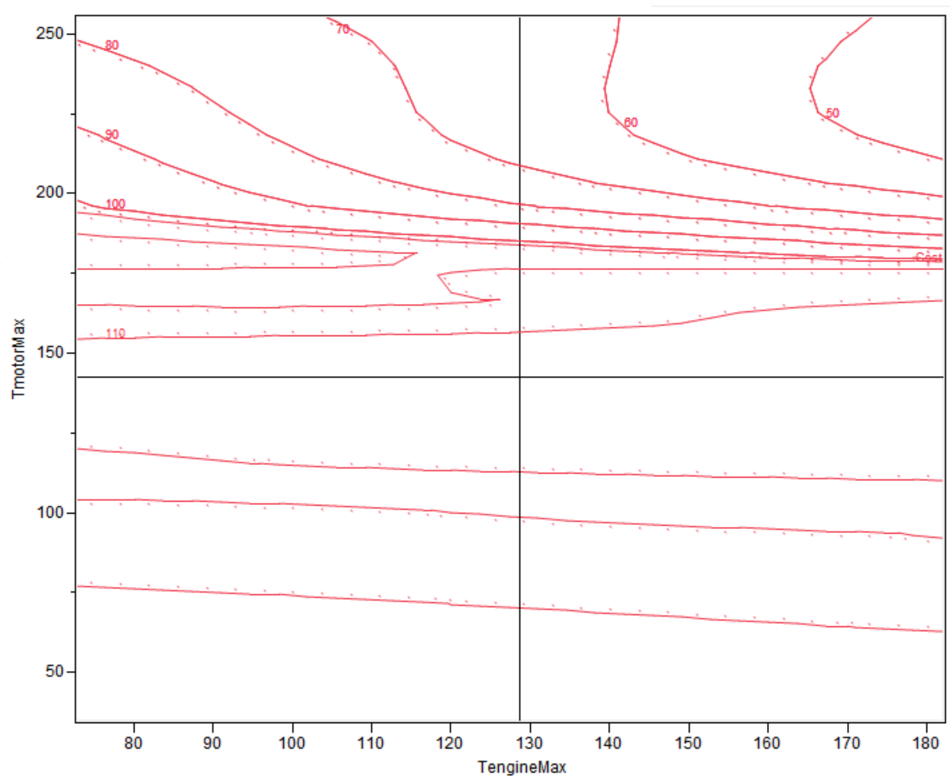

Figure 16 Contour selection of the parallel architecture design space for Engine Max Torque vs. Motor Max Torque vs. Cost

Combining the analysis performed of the design space relative to areas searched, contours, and the objective function formulation we can make a qualitative characterization. The objective function used for the parallel vehicle architecture optimization example discussed throughout the design space analysis uses constraints on the vehicle performance which classifies a vehicle as feasible if they meet the performance requirements and infeasible if they fail to meet the requirements, even infinitesimally. This requirement classifies the objective function as type "1-H" according to Messac [125]. Together, the objective function classification, design space search areas, and the design space sample contours all contribute to validation that global heuristic and stochastic search methods should be applied. Specifically, optimizations solely based on objective function gradient values may get stuck in local minima and unable to locate additional improved designs. Gradient based optimizations would only be capable of achieving a desirable design within the design space shown if it were lucky enough to begin its search near the desired local minima.

6.1.7 Design Results Analysis

With the increased amount of information available as outputs of the simulation optimization in contrast to common vehicle design methods, improved design analysis and decisions can be made. Although concepts can be formulated quickly in conventional vehicle design engineering, decision making and continued iteration towards improved design can be very costly. By including additional considerations and efforts up front in the design process through system engineering methods, reduced risk will result. Through the simulation optimization techniques, desirable optimum designs within selected design space can be quickly identified as well as observing alternative designs in the immediate surroundings of the optimum.

The search methods implemented by all of the optimization algorithms under consideration ensures that increased amounts of design searching will occur at identified desirable solutions. Because of this increase in search around these areas, additional information is available near the identified optimum. In addition to providing an optimal design, the alternative designs identified near the optimum can allow for flexibility in the vehicle design if there are any incorporated objectives and constraints after the initial needs analysis has been defined [71]. These alternative designs are an important design inclusion as they can alleviate the need to return to the needs analysis phase if any alternative designs can accommodate the modified objectives.

6.1.7.1 Design Variable Effects Analysis

A representation of the design variables used in each of the optimizations for the Parallel, Series, Power Split, Conventional Vehicle, and Fuel Cell architecture types are shown in Figure

17, Figure 18, Figure 19, Figure 20, and Figure 21. Statistical information of the optimized vehicle is visible in these figures where the mean, standard deviations, and ranges of each design variable for a chosen cost range are represented. The design variables were used in the optimizations were Maximum allowable Battery State of Charge (SOC Max), Minimum allowable Battery SOC (SOC Min), Maximum Engine Torque (T Engine), Maximum Electric Motor Torque (T Motor), Final Drive Ratio (FDR), Battery Power (Batt Pow), Battery Energy (Batt Ener), Power Split planetary Ratio (PRS), Continuously Variable Transmission starting Ratio (CVTR), and Fuel Cell Power (FC Power). The SOC design variables were used as controller constraints to determine the range of usable batter depth of discharge during the charge sustaining operation. Operational speed ranges for the EM and ICE are held constant through the optimization. The number of design points included in each of the statistical representations is also provided in Figure 17, Figure 18, Figure 19, Figure 20, and Figure 21.

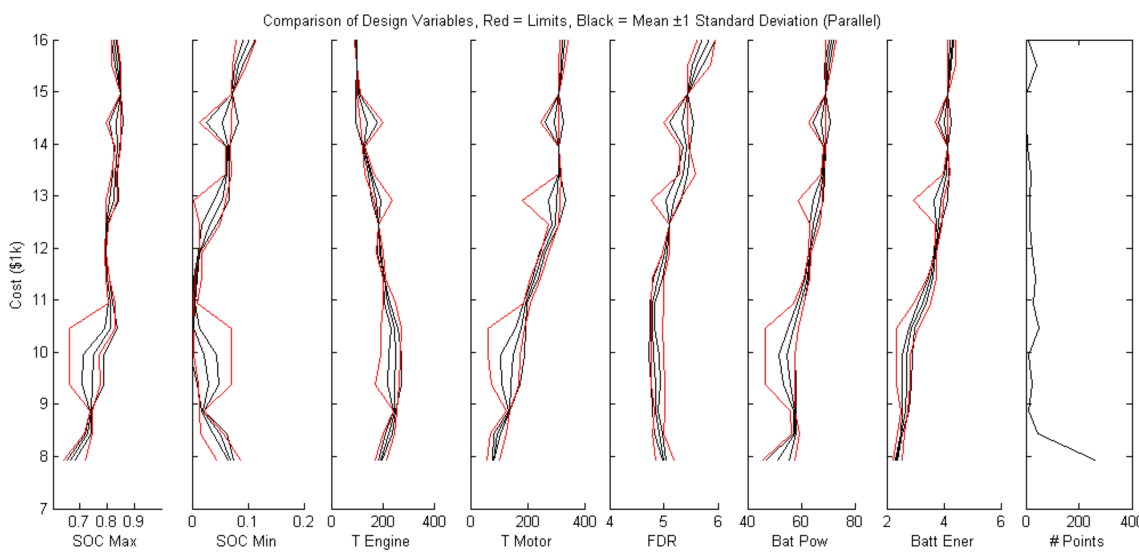

Figure 17 Design variable values vs. cost for Parallel hybrid vehicle architecture.

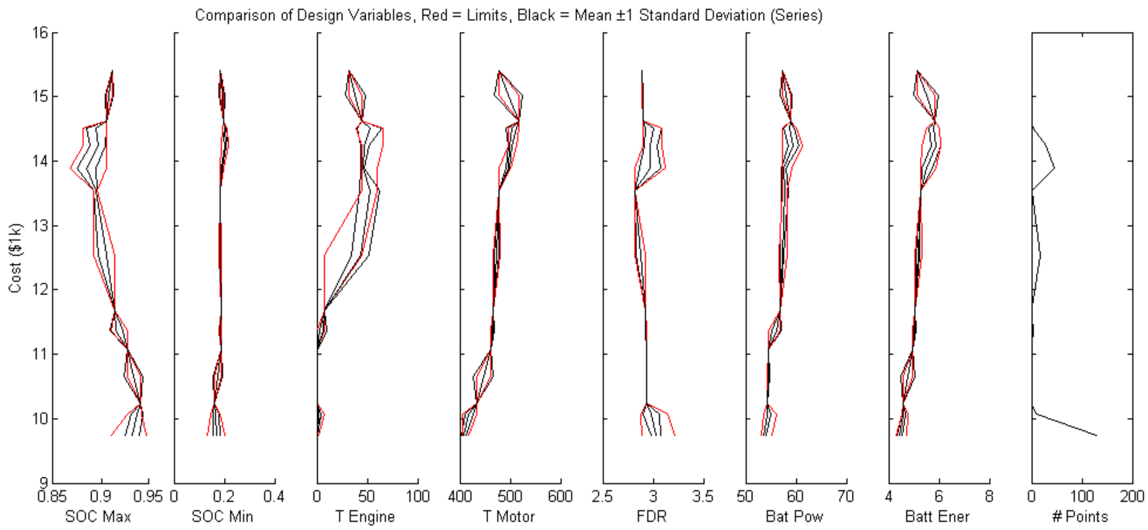

Figure 18 Design variable values vs. cost for Series hybrid vehicle architecture.

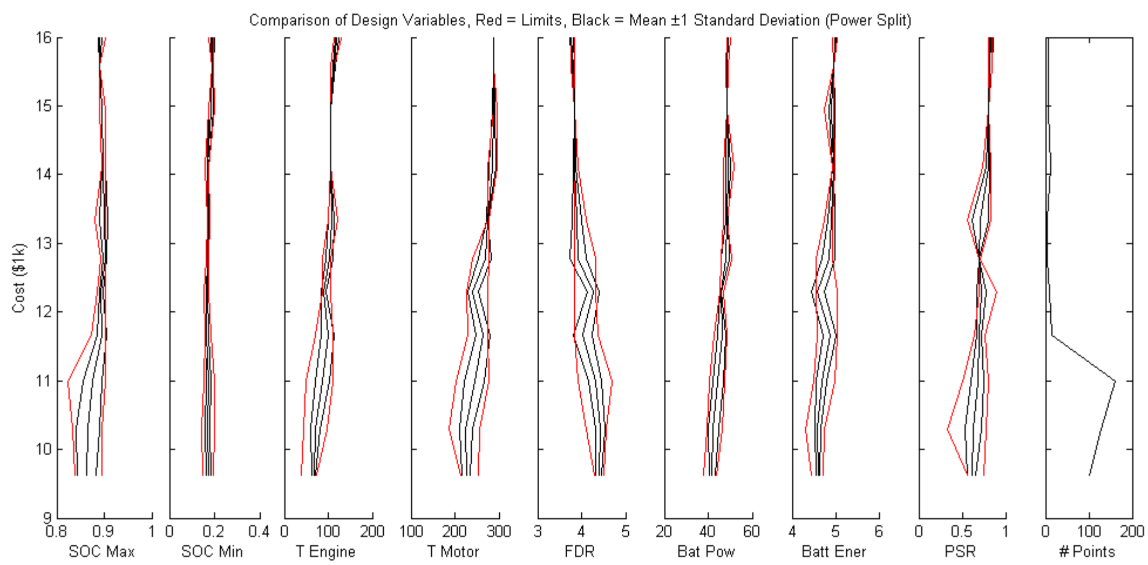

Figure 19 Design variable values vs. cost for Power Split hybrid vehicle architecture

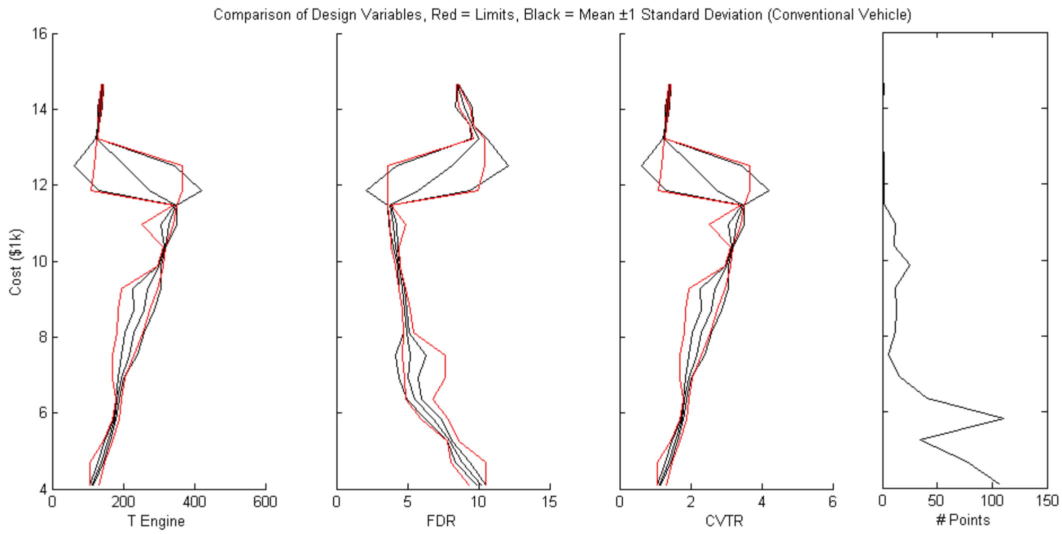

Figure 20 Design variable values vs. cost for a Conventional Vehicle

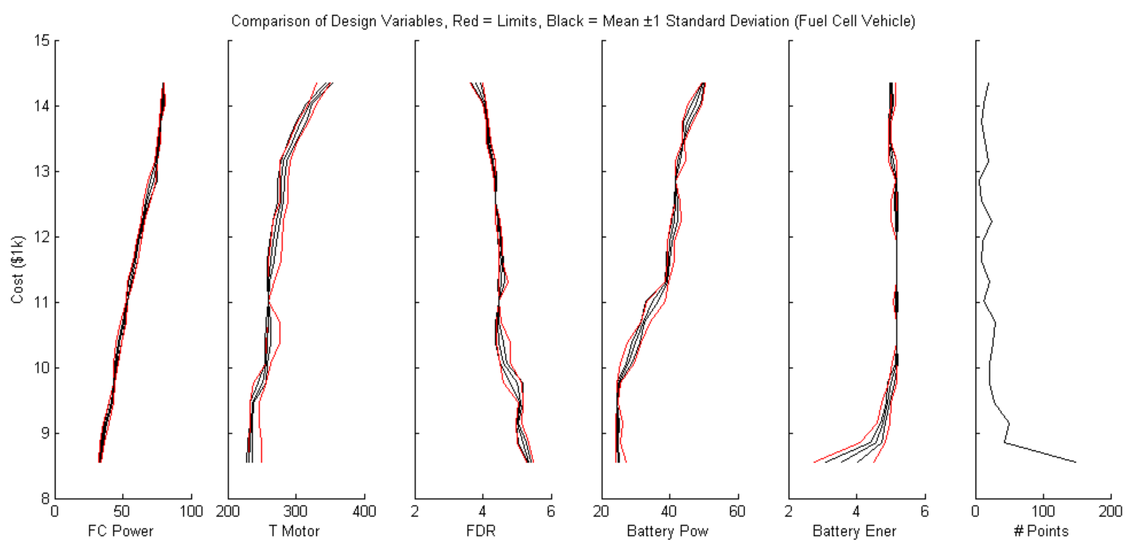

Figure 21 Design variable values vs. cost for a Fuel Cell Vehicle

The specific designs variables that were selected as local minima by each of the optimizations are provided in Table 6. It is important to note that the optimizations use continuous design variables; leading into the possible need to observe variability at constant total cost so that real components can be created if the chosen component design value is not currently available. Changing design variable values may require a need to increase cost to create a "real" vehicle. As is visible in Figure 17, Figure 18, Figure 19, Figure 20, and Figure 21, some of the design variables have larger ranges of values at each of the cost ranges (shown by the range and standard deviation lines), and may be able to represent multiple configurations for relatively no change in component and fuel costs.

Table 6 Comparison of Final Optimization Design Variable Selections

Vehicle	**Total Cost ($)**	**Fuel (mpg)**	**SOC Max (%)**	**SOC Min (%)**	**Engine Torque (Nm)**	**Motor Torque (Nm)**	**FDR (Ratio)**	**Battery Power (kW)**	**Battery Energy (kWhr)**
Parallel	7,682	63	65.9	7.0	184	80	4.99	45.7	2.32
Series	9,569	>>100	94.7	19.1	1	406	3.02	53.6	4.31
Power Split	9,302	>100	84.2	16.7	65	212	4.37	40.2	4.58
CV	3,827	39	NA	NA	108	NA	10.5	NA	NA
FCV	8,3955	58[2]	NA	NA	33[3]	230	5.37	24.8	3.08

For the optimizations performed degradation of battery is not measured; limiting the SOC to certain ranges. This is not considered for this study but can be implemented in a future study. Increased costs associated with changing the allowable ranges of battery SOC can be observed in Figure 17, Figure 18, and Figure 19. It is also apparent from the high fuel economy of the chosen optimum Series and Power Split vehicle designs that a charge depleting vehicle has been created, or is trending towards creation as battery energy becomes greater than fuel energy used. Even with the increased charge depleting operation of the Series and Power Split vehicles, their total costs are greater than that of the optimal Parallel vehicle identified and all of the vehicles are more expensive than the optimized Conventional Vehicle. The optimized Fuel Cell vehicle has a price mid-range between the other vehicle designs but exhibits the added benefit of being insensitive to gasoline costs, which will be explored further in section 4.2.3 Design Sensitivity Analysis.

2 Miles per kilogram

3 Fuel cell kW

6.1.7.2 Design Sensitivity Analysis

When discussing the results of any design effort, particularly in optimization, it is useful to understand the sensitivity of the final design. As an example exploration of the sensitivity of the vehicles the results of a sensitivity analysis are presented for design selections of the optimal design variables as well as assumptions that are made. Assumptions made for gasoline fueling costs as well as ownership time period are provided and analyzed for sensitivity to variation.

To perform a sensitivity analysis on the optimal design variables, each design variable was modified independently of the others and re-simulated to observe the effects on the total vehicle costs for the study presented previously. Design variables were observed for changes +1% and -1% of the optimally chosen values, results are shown in Figure 22, Figure 23, and Figure 24. All operational constraints for the designs such as performance are preserved for the sensitivity analysis.

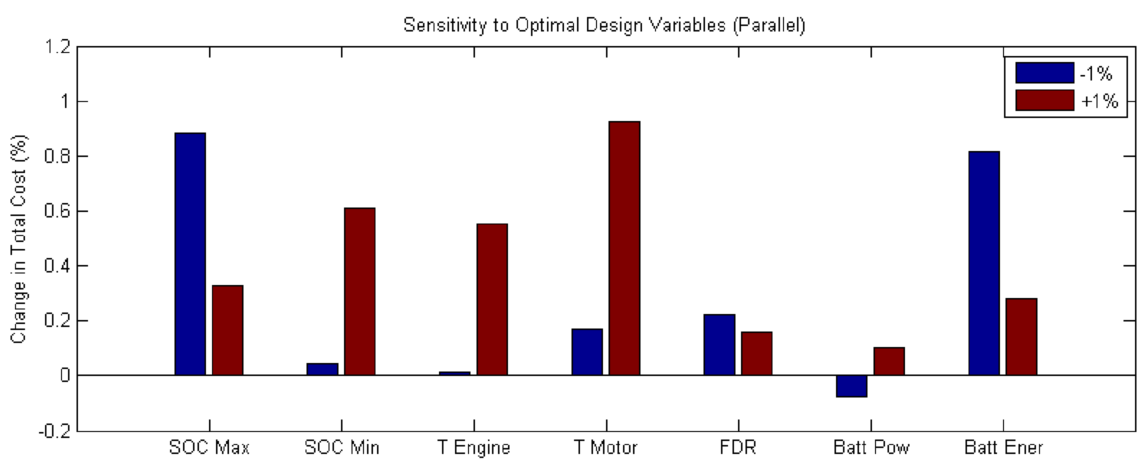

Figure 22 Sensitivity of Parallel vehicle cost to optimal design variable

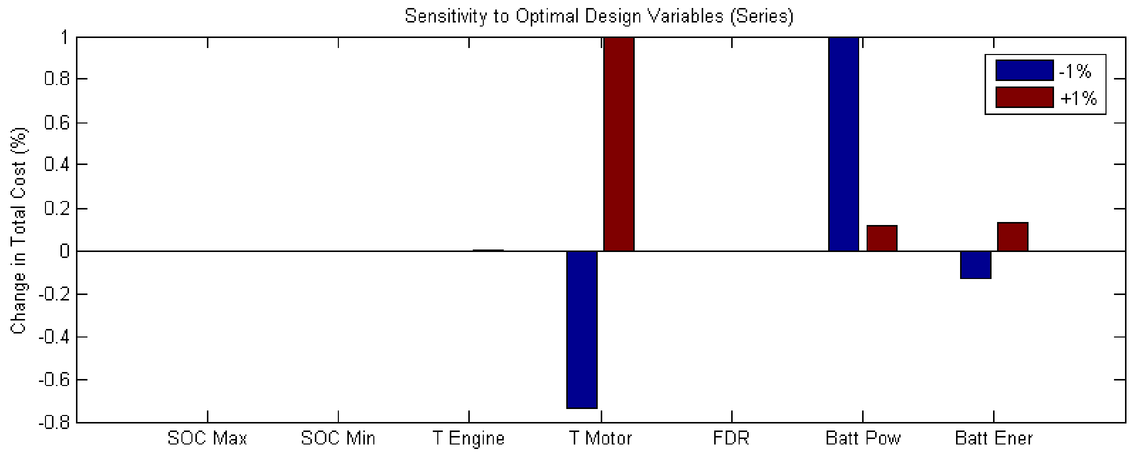

Figure 23 Sensitivity of Series vehicle cost to optimal design variable

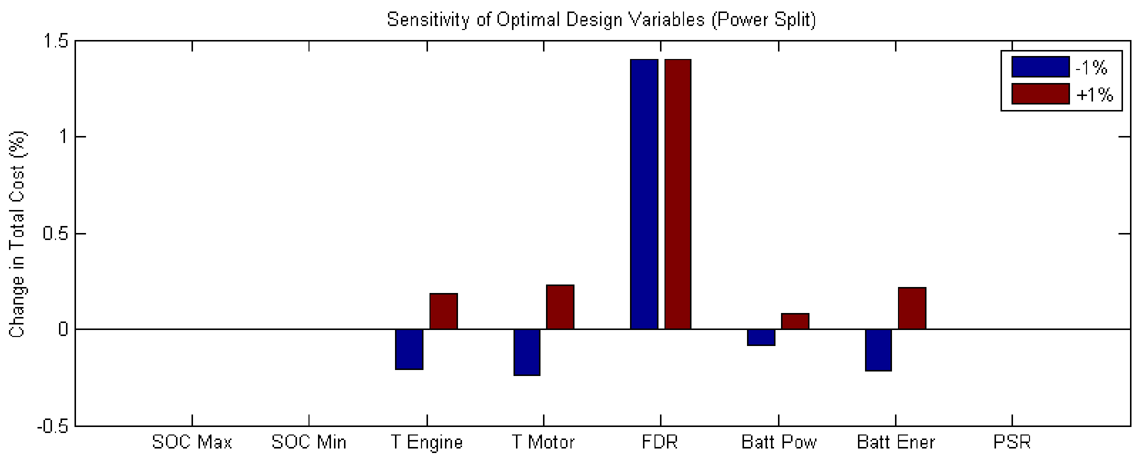

Figure 24 Sensitivity of Power Split vehicle cost to optimal design variable

It can be observed in Figure 22, Figure 23, and Figure 24 that some of the design variables exhibit optimality conditions, such as most of the Parallel vehicle design variables and the Final Drive Ratio in the Power Split vehicle, where any change in design value causes an increase in the total vehicle cost. In contrast, some of the observed sensitivity shows room for additional improvement. The significance of the observed improvements is that the selected design variables are not global optimum but instead were optimal considering the convergence criteria. Additionally, it should be noted in the Series vehicle sensitivity analysis that the values represented as changing +1% for total cost in fact are infeasible as the resulting costs are much greater than +1%. Design variables which do not show values for the optimal sensitivity analysis do not show significant sensitivity to 1% perturbation and may be candidates for alternative optimal designs.

A sensitivity investigation provided in Figure 25 as an extrapolation of the five year cost ownership period optimization (at $3.00/gallon of gasoline) includes three and ten year periods considering fuel costs ranging from $2.00/gallon to $5.00/gallon. Performing direct optimizations for different fuel costs and ownership periods may yield different answers due to differing proportional cost contributions. The sensitivity analysis provides a basis for comparison and further understanding of the effects of the design as it has been defined. Figure 25 shows a relative cost/benefit interaction for owners of the vehicles if they are to sell their vehicle early or keep it for longer (assuming constant 12k miles a year of travel). For example, the total costs of the Parallel and Series type vehicles invert as the fuel costs reach $4.00/gallon for a five year ownership period. Conventional vehicles are shown to be the most sensitive to both ownership period and fuel costs as the slopes and intersects vary the greatest. In contrast, Series vehicles show very little sensitivity due to low fuel consumption and Fuel Cell vehicles are insensitive to gasoline prices for this representation.

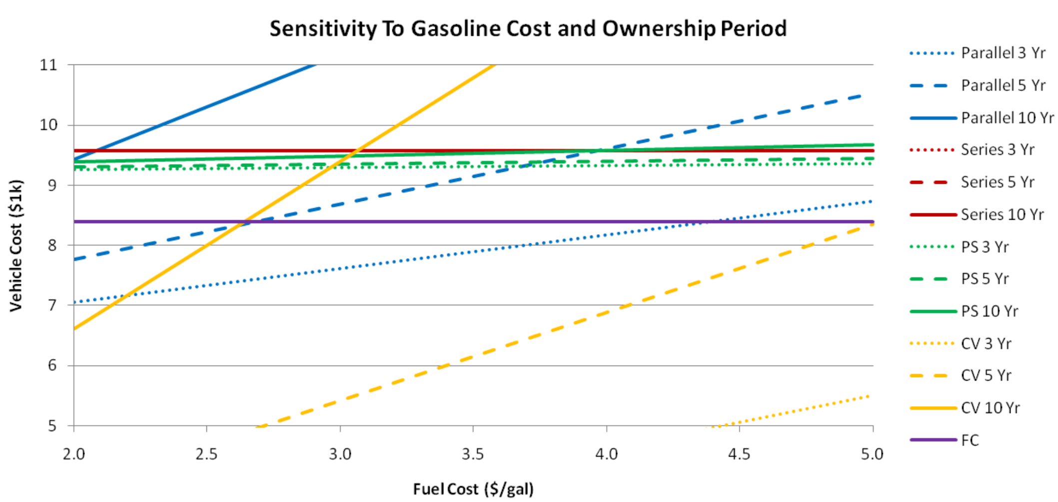

Figure 25 Sensitivity of chosen optimum designs to ownership period and fuel costs.

Sensitivity of additional considerations such as inflation rate and component costs can be performed in similar manners to those provided above but are not provided in this study. In the case of component cost models, relative sensitivity of each optimal component selection can be observed in the figures provided in the previous sections, where components with higher cost contributions are likely more sensitive to variation in component cost assumptions.

All of the analysis performed on the sample vehicles, through simulation optimization, shows the utility of utilizing the optimization tools with well formulated cost functions. Future efforts to improve the control strategies and further refine the design variables, constraints, and objectives selection can result in increased understanding of any complex hybrid vehicle system and design space. This aids in decision making. The specific vehicle design results found through the vehicle optimizations are not intended to represent finality for all vehicles of that architecture type, but simply to allow for a comparison in designs for the constraints formulated in this study.

6.1.7.3 Expanded Optimization Convergence for Alternate Vehicle Model

Although this section has explored simulation optimization using multiple algorithms, the optimality of the identified optimized designs is unknown. To improve upon the previously obtained knowledge base, an additional set of optimizations will be performed while allowing the algorithms to perform a much more thorough search of the design space.

Previous optimization efforts allowed the algorithms to perform 500 function calls for simulating a HEV with a parallel architecture. In this section, a parallel HEV will also be used, but with different control strategies, design space limitations, and design variables. The specific differences between the two vehicle models and cost functions are inconsequential as the objective of this research is to identify optimization algorithms that are robust to automotive simulation and analysis methods. For this section, the four previous investigated optimization algorithms will be allowed to perform 50x more iterations, with a maximum of 25,000 iterations per optimized vehicle.

Each algorithm is applied to the same vehicle model and run for three separate optimizations to allow for both performance and consistency comparison. As mentioned in the previous sections, DIRECT is only run once since it is a deterministic algorithm. The results of the simulation optimizations are presented in Figure 26.

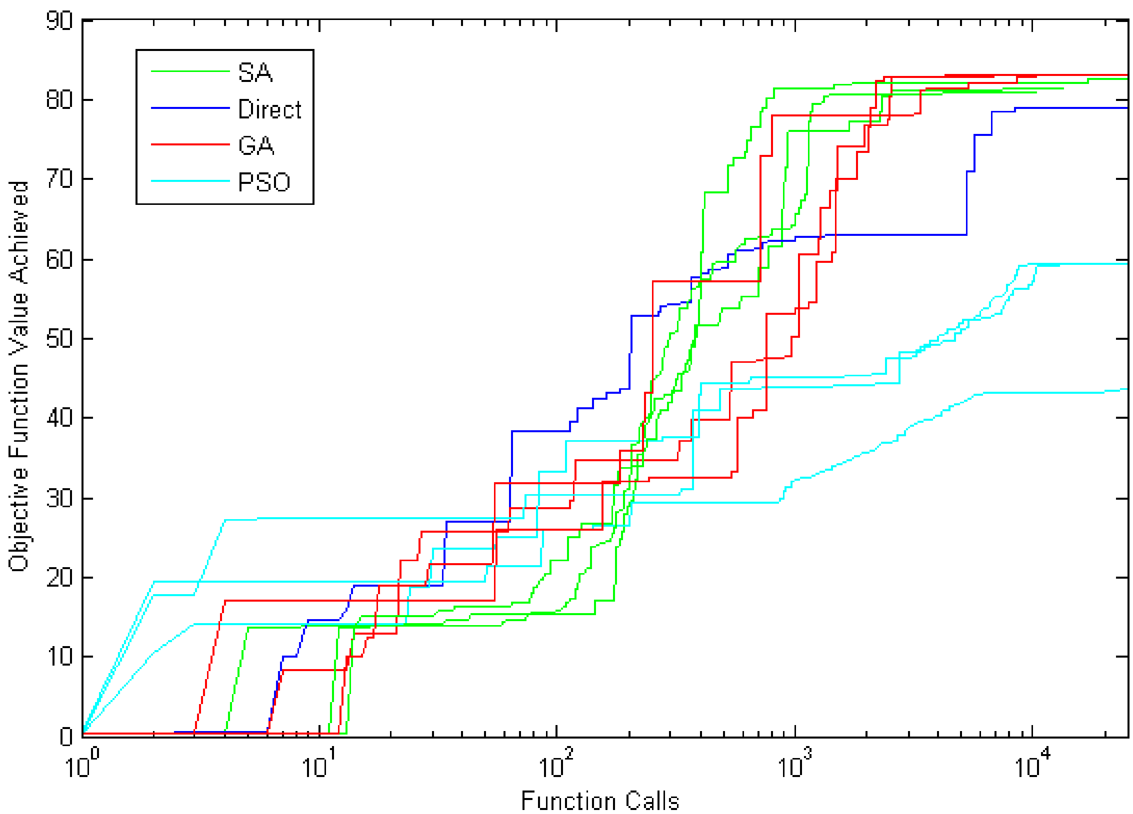

Figure 26 Extended optimization run (function calls on logarithmic scale).

It can be observed in Figure 26 that once again Simulated Annealing (SA) is able to quickly and consistently identify optimized designs. The Genetic Algorithm (GA) is also able to achieve high performance but is less consistent and takes more functions calls than SA. When observing Figure 26 it is important to note that a logarithmic scale is used for function calls (xaxis), demonstrating that it takes approximately 2,000 function calls for GA to reach some of the same solution space as SA. For this model and cost function formulation, DIRECT is able to quickly take the lead in performance (~100 function calls) but falls behind shortly thereafter (~200 function calls) as it's deterministic approach requires it to investigate more 'poor designs' instead of focusing more on low-cost regions of the design space.

6.1.8 Optimization Algorithm Conclusions

Vehicle design is a resource intensive process; incorporating hybridization introduces additional design complexities. By applying systems engineering methods such as objective identification and optimization up-front in the design process it is likely that a desirable solution will be achieved with minimal costs in both time and effort. Through the use of defensible vehicle system simulation, aggregate objective cost functions as system engineering tools can be incorporated to build a better understanding of the design space. Although implementing simulation optimization into vehicular design is not a new concept, applications and utility have been expanded to include additional areas which increase understanding and ability to implement complex designs. A few of the possible assessments that can be taken from a simulation optimization comparison have been provided for sample vehicle architectures, control styles, objectives, and constraints.

A set of vehicle design tools including models, simulations, and optimizations have been presented and explored: providing benefits to future design efforts. Between the four optimization algorithms tested, Simulated Annealing and Genetic Algorithm optimization show more promising performance but function differently within different design efforts.

With proper models, simulations, optimization algorithms, and cost functions almost any vehicle system and design goals can be represented. Future work can be developed to assist designers by analyzing the complex design interactions. This provides not only a reduction of the resources necessary to design an automobile, but also improves the implementation of design objectives in the design construction process.

6.2 Task 2.2 Quantify the Uncertainty in Vehicle Simulation

The design of vehicles, particularly hybrid and other advanced technology vehicles, is typically complex and benefits from systems engineering processes. Vehicle modeling and simulation have become increasingly important system design tools to improve the accuracy, repeatability, and flexibility of the design process. In developing vehicle computational models and simulation, there is an inevitable compromise between the level of detail and the development/computational cost. The tradeoff is specific to the requirements of each vehicle design effort. The assumptions and detail limitations used for vehicle simulations lead to a varying degree of result uncertainty for each design effort. This paper provides a literature review to investigate the state of the art vehicle simulation methods, and quantifies the uncertainty associated with components that are commonly allocated uncertainty. By understanding the inaccuracies and inconsistencies within these studies, improved simulation methods can be proposed. The consequences or accuracy of common assumptions are determined which will aid future simulation efforts as well as provide metrics for evaluating the appropriateness of past efforts. The results of this paper will aid future simulation design efforts and can begin to define standards by which simulation design studies are conducted.

6.2.1 Introduction to Uncertainty in Vehicle Simulation

Computational modeling continues to play an increasing role in the automotive design, development, and evaluation process. As vehicle technologies advance at a quick rate, researchers and manufacturers are challenged with not only keeping up with the state of the art, but also predicting and allowing for future design implementations. Computer based simulation plays an important role in supporting advancement of vehicle technology by assisting in systems engineering design processes. As the level of detail included in vehicle models increases, so does the accuracy of the results; but commonly at the cost of increased computational or system development time.

Many modeling tools have been used to simulate a wide range of vehicle types, technologies, and operational characteristics. Different objectives of these simulations can support different levels of detail and therefore acceptable uncertainty in the results. It is a requirement of the simulation end-user to account for the uncertainty that exists within the systems considered and to understand how uncertainty will contribute to the conclusions of any particular study. Simulations are commonly designed to represent a specific functional characteristic of the vehicles well, but can commonly be misconstrued to represent a wider range of operations than originally intended or validated. As these simulation tools continue to see more use in the academic and industrial automotive design world, they are subjected to more rigorous considerations and applications. The demand for high level details is pushed by an increase in systems engineering design methods that rely heavily on long design explorations through computational based models.

Uncertainty exists in all simulations. The magnitude of this uncertainty must be considered in comparison to the breadth of the results. A number of steps can be taken to evaluate an appropriate method for defining the uncertainty and associating it correctly to the simulation outcomes. The first step in determining uncertainty in a simulation is to classify the type of study being performed. From the type of study performed, objective outputs should be defined. The combination of study and objective type guides the study towards a set of simulation tools that have been specifically designed for that application (whether they exist or not). The second step of determining uncertainty is to define the systems under consideration and their respective data flows (inputs and outputs). The third step requires a detailed evaluation of the equations, assumptions, and parameters implemented in the simulation. The final step requires a validation of the system relative to the type of system and study originally defined. Only after each of these steps have been completed by the simulation developer and approved by the simulation user can the uncertainty of the vehicle simulation be accurately quantified. Each of these steps will be discussed in further detail in the following sections.

6.2.2 General Purpose of Automotive Design Studies

The first step in evaluating uncertainty in vehicle simulation studies is to determine the type of study being performed. The type of study can most easily be classified based on its purpose. Within each of the study types, a different set of considerations must be applied to the uncertainty characteristics. Simulation studies can be classified into three main types:

- Technical rankings
- Representations of futures
- System development and exploration

As a subset of each of the three simulations types listed, simulations studies can be performed based on optimization techniques, design of experiments (DoE) parametric methods, or fixed-point formulations [16]. Optimization techniques can include a variety of algorithms ranging from linear programming to stochastic algorithms [6, 17]. Optimizations commonly define an objective and perform simulation iterations to approach the objective within a specified set of solution requirements. DoE parametric methods operate as design space examination approaches that provide a uniform evaluation of a specified range of parameters, inputs, or assumptions. Optimizations commonly differ from DoE studies as the number of simulation iterations increases, wherein optimizations continuously focus their design explorations and DoE studies remain consistently distributed. Fixed-point formulation studies rely on one or a few pre-determined design space points and usually include much fewer simulation iterations. Fixed-point studies most commonly apply to simulation of a pre-specified system with no design exploration.

Technical ranking (TR) studies consist of simulation efforts aiming to evaluate vehicle options in relation to one another. One or many objective evaluation metrics such as fuel economy, system efficiency, total cost of ownership (TCO), or greenhouse gas emissions (GHG), have commonly been used in previous vehicle simulation studies [5, 9,106, 138]. As with each of the three study types, TR can be performed as an optimization, DoE, or fixed-point study. Optimization TR studies consist of multiple independent optimization of systems such that optimal designs in different categories can be compared. DoE TR studies are performed similarly to optimization TR studies but with a more generalized design space consideration. Fixed-point TR studies intend to compare specific vehicle components or designs such as comparing a specific conventional gasoline vehicle with its matching hybrid model. The TR studies can be particularly sensitive to parameter value specifications but less sensitive to model structure. Details of these sensitivities and sources of uncertainty will be discussed in later sections.

Representations of futures (RoF) studies intend to provide predictions of future technology. These studies can exist in a variety of subsets including economic feasibility, technology limits, technology goals, policy fulfillment, and environmental and social interaction to name a few [18, 19]. RoF studies rely heavily on time sensitive predictions that are proposed to represent a projected future scenario. This type of study usually exists with an initial base simulation for the state of the art (SoA) technology and extends to a future time. Validation of RoF study can only accurately be performed as time progresses, but are commonly tested based on historical cases. RoF studies are asserted to be most sensitive to uncertainty in the assumptions made about future scenarios and definition of the technology SoA.

System development and exploration (SDE) studies aim to investigate the function of the vehicle or its subsystems. SDE studies can include such factors as controller development strategies, component design specifications, trade-off analysis, and scenario implementation. The scenario implementation discussed in the SDE section differs from scenarios from the RoF section as SDE scenarios are based on an available operational environment test case (i.e. different drive cycles) and RoF scenarios are based in a future condition. SDE studies can commonly be associated with Hardware in the Loop (HIL) development and testing. Model structure, including levels or detail, and equation specification, are much more sensitive sources of uncertainty for SDE studies than in the other two study types discussed.

6.2.3 Simulation Tools

Simulation studies can be performed using a number of commercially available and custom vehicle simulation tools. In most cases, each specific tool has been created with the intent of fulfilling a design study type need, but there are alternative options for combining multiple tools or developing a custom tool to meet study specifications. The methods used to develop different simulation tools differ in many ways including numerical solvers, direction of information flow, level or detail, organizational structure, and simulated system type. A few of the available simulation tools available as well as their background formulations are detailed in this section.

A multitude of simulation tools are currently available for design studies. One of the primary differences between these tools is the direction of information flow, or causality. Simulations for vehicles can exist in three configurations: forward facing, backward facing, or non-causal (acausal). All three of these simulation types operate in a time progressive manner, the direction of information flow refers to data within the model.

Forward facing simulations of vehicle systems refers to a model where controls and operation of the subsystems operate in a time-progressive feedback manner. For example, a forward facing vehicle simulation of an electric vehicle driving on a dynamometer schedule would follow the information path shown in Figure 27. A dynamometer drive cycle velocity demand is fed to a system driver that provides a desired torque or throttle demand to the controller. The controller evaluates system limits and transmits the driver demand to the propulsion unit. The propulsion unit supplies tractive effort based on its limited operating conditions as well as calculation of resource/energy use. The resulting vehicle velocity is fed back to the driver and deviations can be accounted for in future commands. Forward facing simulations are generally representative of physical vehicle control systems, and are commonly used for controls development and HIL testing.

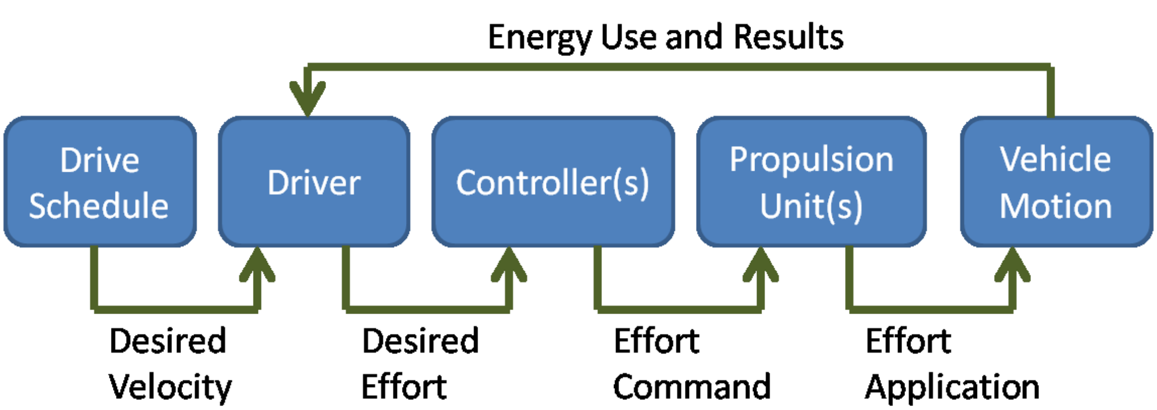

Figure 27 Forward facing simulation flow diagram

Backward facing simulations of vehicles have a similar general structure as forward facing simulations, but with different information flows. In backward facing simulations, shown in Figure 28, it is assumed that a propulsive unit meets drive commands, and energy use can be calculated from the required tractive effort. Backward facing simulations are typically less computationally expensive than forward facing simulations due to a lack of information feedback and complex controls. It is more difficult for backward facing simulations to calculate maximum vehicle performance, such as maximum acceleration, because the simulations are not designed to predict operation of the components at their limits.

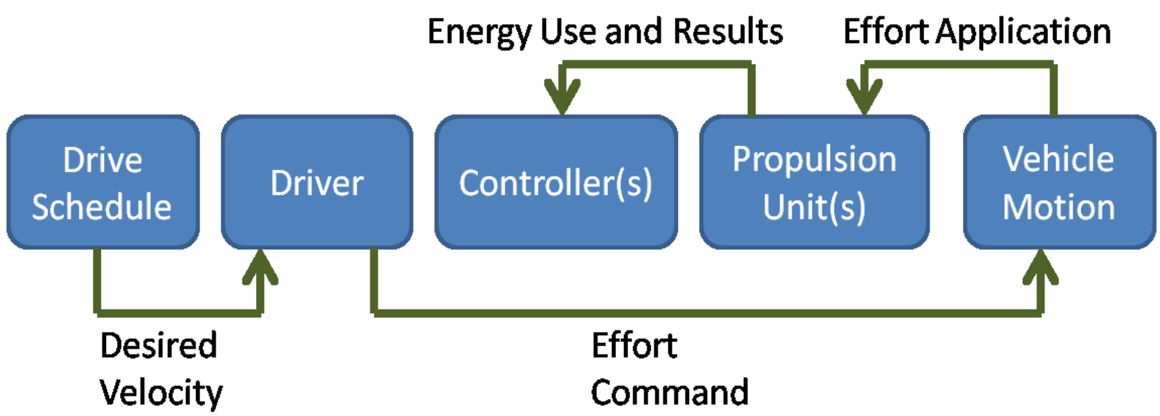

Figure 28 Backward facing simulation flow diagram

Non-causal simulations use a combination of forward and backward facing causality information flow. In some systems this can be implemented through switching calculation type. For example switching information can occur when a backward facing simulation reaches an event in the vehicle simulation where a required component operation is unavailable (e.g. a motor reaches its peak torque). In this case the drive cycle may not be met and continued simulation will require additional controller functionality to get the vehicle operation back on track – which occurs in a forward facing manner until normal operation resumes. An alternative non-causal simulation tool may have a combination of forward and backward facing calculations simultaneously. For example, controllers send commands in a causal information direction, but power flows through an epicyclical gear (planetary) in multiple directions.

Each of the simulation tools available differs in calculation methods and considerations. Table 1 provides a compiled list of some of the simulation tools, the developer of the simulations, and a little information about the simulation methods. Tools should be selected depending on the type of simulation being performed. Additional aspects of each of the simulation tools and how they relate to the uncertainty of the vehicle simulations will be described in later sections.

6.2.4 Types of Uncertainty

Uncertainty has classically been defined in many different ways depending on the systems that provide and measure the uncertainty [37]. The primary focus of this section is to understand the uncertainty that exists in vehicle simulations studies. Vehicle simulation studies most directly relate to uncertainties in simulation and computation methods, data acquisition from physical systems, and equation formulation. Secondary sources of uncertainty such as environmental random conditions, human error, and future forecasting must also be included but interact with the system at a higher level and can be ignored for some studies.

Uncertainty in vehicle simulations has been classified into three groups [26]:

- Type-1 uncertainty: Variability of input or parameters. Type-1 uncertainty is usually handled by providing distribution functions of the defined inputs and parameters when available.
- Type-2 uncertainty: Similar to Type-1 uncertainty where variability exists in the inputs and parameters but without a known distribution. Fuzzy logic and evidence theory have been used for solutions.

- Type-3 uncertainty: Uncertainty from an unknown process. This type of uncertainty is the most difficult to find solutions for.

Uncertainty can also be classified as either aleatory or epistemic [37]. Aleatory uncertainty pertains to information that can be represented by a distribution; epistemic refers to completely unknown factors. Type-1 uncertainty can be classified as aleatory, Type-3 uncertainty can be classified as epistemic, with enough testing it is likely that Type-2 uncertainty can also be described using a distribution of data; classifying it in the aleatory uncertainty.

Measuring error and uncertainty should include an understanding of the accuracy and precision of the data sets, wherein accuracy represents the measured difference between a predicted and measured value, precisions compares the distribution of the predicted and measured values. Models and simulations can be accurate without being precise or vice-versa. The measures of accuracy and precision can aid in identifying the sources of uncertainty. For example, an inaccurate but precise simulation may account for input distributions well, but use a parameter value that deviates from the value that should be used.

Control and dynamic systems define uncertainty by a difference between models and reality [37]. Error is the measure of the difference between some observed value and its prediction from a model or simulation. The uncertainty of simulations can be determined through combining the input parameter distributions, validation error, numerical approximations, and the other uncertainty types as presented in the following sections of this paper.

6.2.5 Sources of Uncertainty

Uncertainty in vehicle simulation studies usually occurs from multiple sources. It is the responsibility of researchers to identify the primary sources of uncertainty in the simulation methods they are using and ensure that the uncertainty is properly accounted for in the simulation and results. A few of the identifiable sources of uncertainty include: system dynamics, numerical methods, parameters, assumptions, and validation criteria [38]. These five sources of uncertainty each fit into different portions of a simulation study as shown in Figure 29.

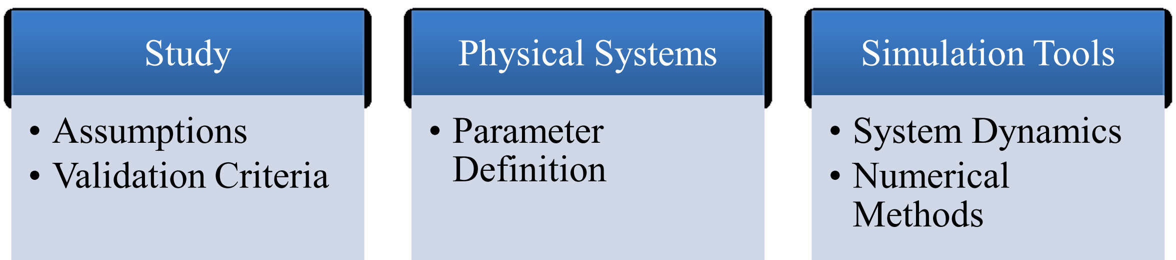

Figure 29 Sources of uncertainty in vehicle simulation.

6.2.5.1 System Dynamics Uncertainty

Real world systems are highly dynamic. As these systems are modeled in a computational domain considerations must be made as to the frequency of solving different system equations. Continuous time step and fixed time step computational solvers have been used in vehicle simulation studies and will be discussed in more detail. Before selecting which solver should be used, an understanding of the rate of variable change in dynamic systems must be considered.

In the real world, changes in systems occur at an infinitesimally small time scale. A common way of considering these systems is to make measurements of the systems based on common unit measurements. For example, even though ambient temperature can be measured to as many significant figures as the measurement device allows, for vehicle systems only two significant figures are commonly used because the performance of most automotive systems is insensitive to small changes in temperature. This means that the computation of the ambient temperature in a vehicle system simulation only needs to occur such that changes can be accounted for at the specified level of detail.

Table 7 dynamic time scales for fuel cell vehicles systems and hybrid vehicle

Fuel Cell Vehicle System	Dynamic Time Scale
Electrochemistry	1xE-19 seconds
Hydrogen and air manifolds	1xE-1 seconds
Flow control	1xE0 seconds
Vehicle inertial dynamics	1xE1 seconds
Cell and stack temperature	1xE2 seconds

HEV System	Dynamic Time Scale
Pedal position	1xE-3 seconds
Vehicle speeds	1xE-1 seconds
ICE speed	1xE-2 seconds
EM speed	1xE-2 seconds
EM torque	1xE-2 seconds

One way of determining the level of detail considered in system dynamics is to evaluate the compounded effect on computational solutions. Significant figure inclusion should be determined such that effects can be measured in the outputs and the magnitude of the uncertainty is less than the dynamic detail. For example, measuring the same ambient temperature introduced above to five significant figures is unnecessary if the uncertainty occurs up to one significant figure. Table 7 provides a few suggested dynamic time scales for system simulation from fuel cell [39] and hybrid electric vehicles [40]. Dynamic time scales should be determined for each calculation made in a simulation. As an example, a DC/DC converter operating at 50 kHz should not be modeled to provide dynamic output at 1Hz. Some subsystem time scales are more immediately identifiable such as Internal Combustion Engine (ICE) torque slew rates and switching frequencies, where others such as electrochemical reaction rates and thermodynamic interactions can be complex to implement without high levels of detail.

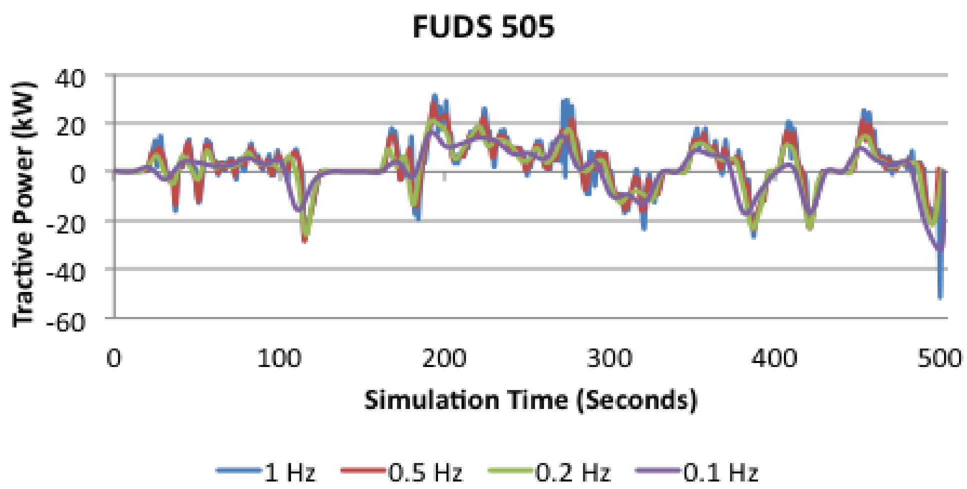

Figure 30 Comparison of simulation time step effect on power requirements.

Uncertainty occurs in dynamic vehicle simulation studies when the time scale of the systems is not accounted for. If the simulation calculation occurs at a slower rate than the dynamics of the system, then functional details can be lost. Loss of detail in the vehicle simulation leads to uncertainty. For example, if electric motor (EM) torque output is simulated at 0.5 Hz and the motor is capable of performing at 1 Hz, then important operational characteristics of the EM system may be absent from the simulation results. Figure 30 shows a sample comparison of a typical compact vehicle simulated on the FUDS 505 drive cycle at different frequencies (1Hz base frequency). Table 8 shows the results of the vehicle simulation from Figure 30. It can be seen that removing dynamics from the system greatly influences energy use of the simulation, but does not affect the total distance traveled as much. It should be noted that both the energy and distance observed are calculated by cumulative integration of other values. The difference in dynamic influence is directly related to the rates at which each sub-value changes (power and velocity).

Table 8 Comparison of dynamic frequency effects on energy use and distance traveled.

Dynamic Frequency	Energy (kWh)		Distance (km)	
	Value	Error	Value	Error
1 Hz	0.4879	-	5.77	-
0.5 Hz	0.2261	54%	5.77	0.01%
0.2 Hz	0.0733	85%	5.79	-0.31%
0.1 Hz	0.0325	93%	5.81	-0.78%

A simplified comparison of simulation uncertainty incorporating system dynamics and simulation calculation causality is shown in Figure 31. The uncertainty shown in Figure 31 is representative of validation error values found for simulation tools in each category when evaluating the prediction of simulated vehicle MPG. It can be seen in Figure 31 that as the complexity of the system dynamics and the model increases, the simulation uncertainty decreases, but at a decaying rate. The decaying rate exemplifies the diminishing returns on accuracy for increased simulation tool complexity.

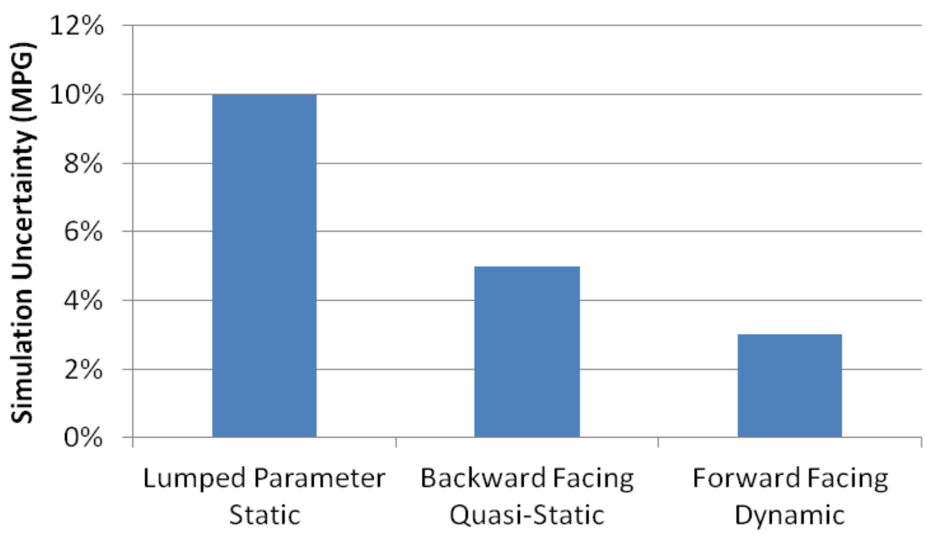

Figure 31 Comparison of relative uncertainty associated with simulation methods for MPG.

6.2.5.2 Numerical Methods Uncertainty

The numerical methods used to define a vehicle simulation can greatly affect the uncertainty of the solutions. The specific numerical methods discussed in this section pertain to the numerical approximation of physical systems as well as the simulation solvers used to perform the computations [41].

Numerical approximation of real systems must occur in vehicle simulations. On a broad spectrum, any equation used to describe a physical system is in some way an approximation. Equations are defined for systems based on an inability to disprove, not on the ability to prove. Equations ranging from Kirkoff's Laws for electrical systems to aerodynamic drag are all approximations of real systems and have some inherent uncertainty, albeit usually very small. Progressing beyond physical system equations, it is not uncommon for vehicle system models to incorporate additional system numerical approximation such as quasi-static lookup tables and functional surface fits. When using these approximations the data supplied to formulating the initial approximation is finite and unable to represent every possible operational state of the system. For example, lookup tables are commonly used for efficiency approximation of ICE operation. Data points are supplied from test benches at finite points along predetermined dimensions such as speed and load. Although the data points may be considered to have low uncertainty based on the data acquisition method used, the operation of the ICE at conditions that lie between data points provide some level of uncertainty. It is usually the case that a very limited number of data points are supplied to these maps that immediately reduces the accuracy of the simulation, as data located between measured points is probabilistic. Increasing the density of the data points taken can improve accuracy but can never absolutely match the operation of the physical system even in steady state considerations. A study performed by

Echter [42] compares test data with simulated engine fuel maps for large diesels. Using only the engine subcomponents of the model, and feeding the test data engine speed and load directly into the simulation, fuel consumption (L/100km) errors averaging 2.7% up to 7.7% were found. These errors have been associated directly with missed system dynamics due to the numerical approximation of the system.

As was mentioned previously in this paper, simulation tools can use fixed or continuous time step equation solvers. Fixed time step solvers take predefined advancements in simulation time space and calculate solutions to the modeled equations at each progressive state. Variable time step solvers have the ability to dynamically calculate the necessary time step required to complete a calculation based on the dynamic response of the system. Systems and events that exhibit fast response, such as in hydraulic or electrochemical systems, can be calculated with appropriate computation when necessary since the time step taken is continuously changing to either increase or decrease the time scale considered. Variable time step solution methods commonly require increased amounts of computation when compared to fixed time step systems, although limits to the scale of step taken can be applied to reduce this [43].

An example of a widely used vehicle simulation tool is Matlab/Simulink. Simulink has a variety of built in solver options including fixed and continuous time steps. Within the continuous time step simulation solvers, tests have been performed and recommendations made as to which systems the solvers should be used in. A simple comparison of the solvers available in Simulink is shown in Table 9 [40]. Many of the solvers available for vehicle simulation have calculation error tolerances that can be set by the user. These tolerances are used to determine calculation convergence at each time step for variable time step simulations. Simulations should be considered to always have uncertainty greater than the calculation error tolerance because of the compounding effect of solver error and other simulation uncertainty sources.

Table 9 Available Matlab/Simulink solvers and description of use.

Solver	Problem Type	Order of Accuracy	When to Use
ode45	Non-stiff	Medium	Most of the time. This should be the first solver to try.
ode23	Non-stiff	Low	For problems with crude error tolerances or for solving moderately stiff problems.
ode113	Non-stiff	Low to high	For problems with stringent error tolerances or for solving computationally intensive problems.
ode15s	Stiff	Low to medium	If ode45 is slow because the problem is stiff.
ode23s	Stiff	Low	If using crude error tolerances to solve stiff systems and the mass matrix is constant.
ode23t	Moderately stiff	Low	For moderately stiff problems if you need a solution without numerical damping.
ode23tb	Stiff	Low	If using crude error tolerances to solve stiff problems.

To demonstrate the numerical uncertainty found using different numerical solvers, a Matlab/Simulink demo simulation was used. The demo simulation was developed to represent a HEV powertrain. The EM was observed operating over 100 seconds of a FUDS drive cycle for three different solvers. The energy use results of the simulations are shown in Table 10. Although the errors are fairly low, it should be noted that these are integrated values. The errors present in the example simulations would continue to propagate as longer dynamic simulations progress. The ode113 solver calculated value is set as the base value because of its claim for high accuracy.

Table 10 Energy use of an EM using different numerical solvers.

Solver	Amp-Seconds	Difference
ode113	6.5614	-
ode45	6.5626	-0.019%
ode23s	6.5145	0.714%

6.2.5.3 Parameter Definition Uncertainty

Depending on the study, uncertainty can come from a variety of sources. Parameters used in a simulation have error resulting from the measurement of the representative vehicle (i.e. mass or frontal area). Also, evaluation metric parameters such as component costs or upstream GHG emissions may contain error. Identifying errors within simulation, after simulation, or in both situations is a necessary task to quantifying the total simulation study uncertainty [16, 44]. Sources or parameter uncertainty can occur through the measurement of the parameter and in the definition and implementation of the parameter.

Parameter uncertainty that occurs on the input side of the simulation is associated with the definition of parameter values to be used in the simulation [45]. This source of uncertainty can arise from an inability to accurately measure a desired parameter, such as a fluid heat capacitance, without allocating for a wide range of assumptions. These types of parameter definitions are commonly prescribed at standard operating conditions for the vehicle system, but must be identified as sources of uncertainty, particularly if the system encounters non-standard operating conditions. Additionally, there is a source of uncertainty when taking measurements of desired parameters in that the specific measurement may not apply correctly to future systems [44]. An example of this can be presented though manufacturing inconsistencies of hybrid vehicle systems. When automotive battery packs are manufactured, individual cells are combined to form a completed unit. Due to manufacturing methods and material variation, the exact power and energy capacity of each cell may be slightly different. To minimize cell failure due to imbalances within the pack, each cell is sorted according to its performance and alike cells are combined to form a battery pack. This method attempts to minimize inconsistency between successive battery pack characteristics, but the inconsistency cannot be eliminated.

Implementation of parameters in vehicle simulation studies is a source for uncertainty in addition to the formulation of the parameters through measurement. Improved methods of allocating uncertainty exist in parameter definition such as applying a distribution to a given parameter. But, if the applied distribution is not used in the simulation study the uncertainty of the results increases. Approximations are not uncommon in parameter definition, but should be used sparingly and impacts should be measured. One common source of approximation uncertainty for parameters is scaling functions [46]. Many vehicle simulation tools allow for subsystem components to be scaled based on a defined factor, for example EM power scaling. The amount of uncertainty propagated through the simulation is sensitive to the inclusion of important factors in the scaling approximation. In the previous EM example where performance maps are used, if the motor power rating is scaled, correct peak torques, corner speed, efficiency, mass, and inertia calculations should also be performed to determine new operational characteristics. Although these scaling factors can be helpful in approximating a range of systems, as was discussed in the Numerical Methods Uncertainty section, uncertainty increases as data approximations are used further away from the measured values.

As an example of the effects of input parameter uncertainty, a midsized HEV was modeled using Autonomie simulated over the HWFET drive cycle. With the model, three simulations were run using the default ICE power and scaled powers 5% greater and 5% less than the default value. The resulting changes in MPG, CO_2 emissions, and electricity use are shown in Figure 32. For changes in ICE power of 5%, all of the observed simulation results changed less than 1.5%; each with different magnitudes depending how sensitive the calculation is to the input parameter under consideration. Parameter uncertainty for model inputs can be accounted for most easily by including parameter distributions. Delorme [18] uses the input parameter distributions in a RoF studies to compare possible future fuels for passenger vehicles, accounting for uncertainty in the prediction of future technology scenarios.

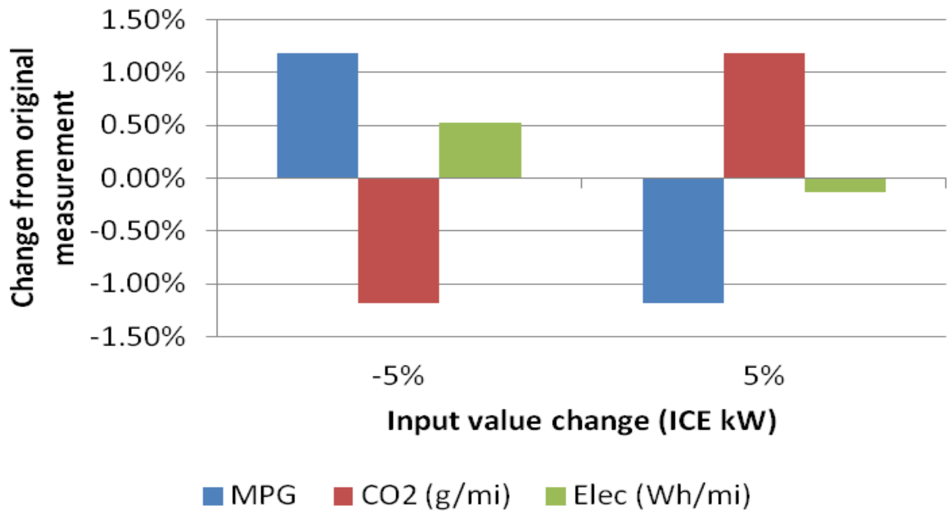

Figure 32 Autonomie input parameter (ICE Power) variation effects.

6.2.5.4 Uncertainty Associated with Assumptions and Simplifications

A few of the sources of uncertainty in vehicle simulations associated with assumption include constraints, initial and boundary conditions, and stochastic environments. To improve simulation, boundary conditions can be applied to vehicle simulation subsystems and components to either limit operation based on control strategy, or to enforce physical limitations that have been observed during data acquisition but have not accurately been modeled. An example of boundary conditions includes ICE fuel injection rates. In vehicle simulations without highly detailed ICE models fuel rate functions or quasi-static maps have been used [42]. To account for situations where the engine may behave differently than standard conditions allow, such as over speeding or rotating backwards, constraints are applied to mitigate inaccuracy [44]. These constraints may not be physically accurate of the system being modeled.

Another type of uncertainty associated with constraints assumptions involves the design space. When DoE and optimization design studies are performed there is a possibility that limits will be applied to the allowable range of design variables [6]. Occasionally these assumed limitations can have functional requirements, such as having an ICE with a negative power rating, but other times they may intend to limit the scope of the design space exploration such as not considering an ICE greater than 400 kW. Uncertainty in design space limitations of the second type can be identified particularly in RoF and TR studies because possible desirable designs may be excluded from the study unintentionally.

Initial conditions and simulation environment assumptions affect study uncertainty similar to parametric definitions, but differ in application due to increased amounts of randomness. One common example of this type of uncertainty lies in vehicle-road interactions. Many vehicle simulation design studies assume a uniform road surface with ideal friction interactions. More advanced vehicle models attempt to simulate road slip conditions such as uniform pavement, gravel, or even ice but require higher computational costs due to increased detail. Exclusion of stochastic road environment conditions has been shown to cause certain amounts of uncertainty in many of the design objectives such as fuel economy, controls system design, and system robustness. In reality minor imperfections cause systems such as traction control to function that can greatly change vehicle operational characteristics. External dynamics such as cornering, which cause power distribution changes in the differential, are usually neglected. Most simulations are assumed to occur in a straight line over drive schedules that are not representative of realistic vehicle operation. Gopal et al shows with multiple simulation tools that curved vehicle paths can reduce vehicle fuel economy (MPG) by ~25% for the same operating speed [27].

6.2.5.5 Validation Criteria Uncertainty

An area of uncertainty that can be easily overlooked is the evaluation of vehicle simulations with validation criteria. Whether validation of a simulation is considered at the subsystem component of vehicle system level, uncertainty must be considered on both the model side and the physical system side [41]. The uncertainty that can be associated with data acquisition from physical systems was already discussed briefly throughout previous paragraphs. Validation criteria uncertainty sources are more concerned with the methods of validation.

When performing simulation validation, it is not enough to just compare simulation and test data graphically. Graphical comparisons of data sets may appear reassuring to an observer, but offer no mathematical basis for an accurate validation. Advancing slightly beyond simple graphical comparison, linear fitting of simulated and test data correlations can offer a metric for measuring accuracy and precision of simulation tools. Statistical t-tests and p-value analysis offers another metric for analysis. Rebba et al [47] suggests the use of Bayesian methods to ensure statistical comparisons between test and simulation data that is defensible. Very few of the vehicle design simulation tools and studies examined as background for this paper included statistically defensible validation methods beyond visual comparison.

The method of simulation validation performed should always be associated with the objective outputs of the simulation study. For example, if a study is focused on evaluating fuel economy of different vehicle designs, then the simulations should be validated through comparisons of simulated and real vehicle fuel economy. Brooker et al [30] show validation performed for NREL's Future Automotive Systems Technology Simulator (FASTSim) using a variety of vehicle architectures, allowing for extensibility of applying the simulation tool to many vehicles. All except for one of the vehicle validated for FASTSim produced fuel consumption errors within 10% as shown in Figure 33. As another example, if a design study aims to conduct control system development, then validation should be performed on the physical system relative to changes in control strategy. For a controls system validation, it is likely that time and event specific operation should be validated instead of only end-of-test accumulated values such as fuel economy. Mismatching of simulation validation criteria with study objectives can be identified as a major source of uncertainty in many studies. For example, the vehicle modeling and simulation tools ADVISOR and PSAT have been developed and validated with vehicle fuel economy studies [22, 34, 48]. Researchers and other vehicle simulators continue to perform studies on vehicle control system development with the simulation tools listed above, without proper validation of the simulations representing their systems.

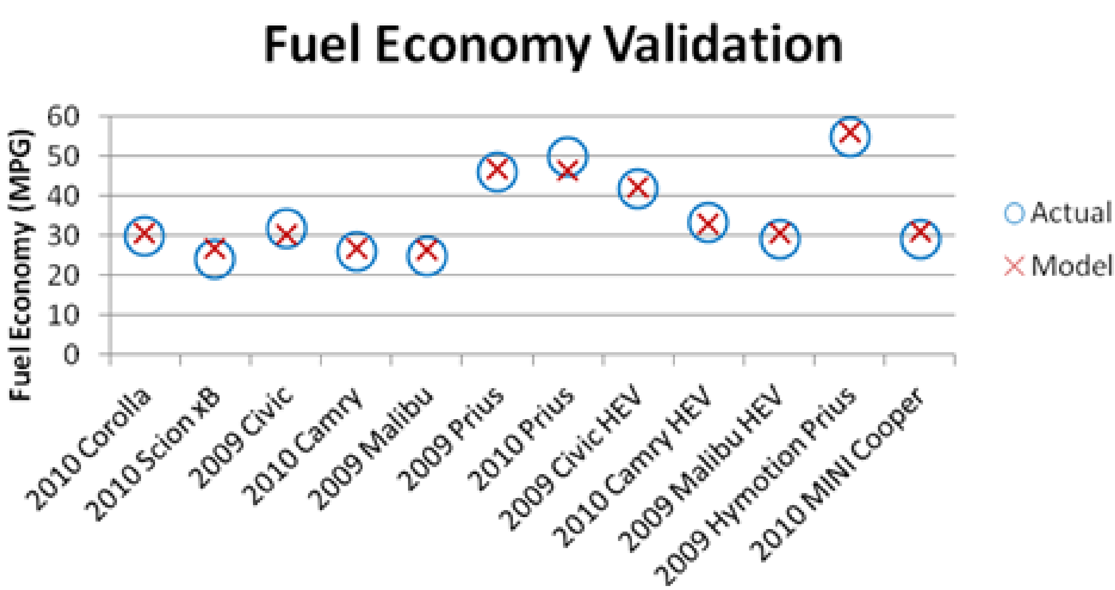

Figure 33 Validation of FASTSim for fuel economy (image courtesy Aaron Brooker, NREL).

A second validation criteria area of uncertainty lies in the correctness of the criteria. A prominent example is the simulation of vehicles over limited drive cycles. Studies that conduct vehicle simulation over drive cycles must be careful to consider that the results are only representative of the drive conditions simulated. Thus, a study performed for vehicles operating on a city driving schedule cannot claim that the results are representative for all operating conditions. Additionally, the validation of simulation using driving cycles is difficult because of experimental uncertainty including human error. Unless validation vehicle systems are tested solely with HIL and computer controls, dynamometer or real world driving should be considered a source of uncertainty when comparing simulation and physical validation criteria.

A few simulation tools have been validated using other simulations tools [34, 49, 50]. This approach can be successful if the validation criteria for the original simulation tool and the second simulation tool match, but can lead to increased uncertainty if not. When simulation models are validated using other simulation models, there is an advantage of being able to compare transient simulation values directly and observe more variables than may be available from vehicle testing efforts. The problem with compounding validation is that uncertainty can be misleading. For example, PAMVEC was validated using ADVISOR [34]. There was a 20% error between ADVISOR's total energy use calculations and PAMVEC's simulation of similar vehicles. ADVISOR is claimed to have 10% uncertainty for total energy use, creating the potential for ~30% total energy use uncertainty through error compounding in the two simulation tools. To reduce this uncertainty PAMVEC was also validated using vehicle test data, showing ~10% error for fuel consumption (MPG equivalent) for a fuel cell HEV.

6.2.6 Measurement of Uncertainty

Uncertainty should be measured based on the objective evaluation metric. Within the vehicle study type performed, objectives should have been defined at the beginning of the study process. The same metrics that are being used to quantify the outcome of the simulations should be used for validation and uncertainty quantification.

Researchers using vehicle simulation tools should be aware of the uncertainty that exists in the models they incorporate into studies. A broad investigation to find documentation for validation and uncertainty in different simulations tools returns limited information. Table 11 lists a few of the validation error values for different simulation tools. The objective evaluation metric used to perform the validation for each tool is also listed. In each validation case, different assumptions are inherent such as the drive cycle used, environmental conditions, etcetera; the assumptions are not included in Table 11 and should be investigated for specific studies.

Table 11 Validation errors found for specific metrics of different simulation tools.

Simulation Tool	Objective Evaluation Metric	Validation Error
ADVISOR [22, 34]	Wh/mi, MPG	10%, 5%
AVL CRUISE [28, 51]	0-60, CO_2, L/100km	2%, 3%, 3%
CAR [24]	CV MPG, HEV MPG	10%, 1%
CarSim [22]	Wh/mi	5%
EPA MOVES [29]	Emissions	10%
FASTSim [30]	MPG	10%
HEVSIM [31]	Transient Values	5%
HVEC [33]	MPG, Acceleration	10%, 10%
Modelica [6]	Wh/mi, MPG	5%, 5%
PAMVEC [34]	Wh/mi, MPG	20%, 10%
PSAT [48]	CV MPG, HEV MPG	2%, 5%

The simulation tools listed in Table 11 have been used in a variety of vehicle design studies. A few of the studies that have been documented in literature are listed in Table 12 along with the design objective evaluation metrics, simulation tools, and results margins. The results margins for these studies represent the difference between design options within the study. For some of the studies the option is choosing between vehicle technologies or fuels, for others it can be improved control methods over a baseline vehicle, etc. The results margin is important in these studies because in order for the researcher to present a valid conclusion, the difference between two design options must be greater than the uncertainty for the respective simulation tool. If the results margin is comparable in magnitude to the validation error (and thus the uncertainty) then there is a probability that the results of the study may be subsumed by simulation uncertainty. Figure 34 shows a graphical representation of how results margins and simulation uncertainty interact to determine validity of solutions. The existence of the non-conclusive region for the overlapping uncertainty within the results margin is undesirable. Fully defensible solutions would not contain a non-conclusive region.

Table 12 Comparison of vehicle simulation studies and results margins.

Study	Objective Evaluation Metric	Simulation Tool	Results Margins
Demirdoven [52]	WTW Fuel	ADVISOR	5%
Wu [53]	Drivetrain Cost	ADVISOR	10%
Gao [54]	City MPG, Hwy MPG	ADVISOR	23%, 7%
Wipke [23]	MPG	ADVISOR	17%-24%
Sangtarash [55]	L/100km	AVL CRUISE	12%-34%
Ye [56]	Fuel Economy	LabVIEW	17%
Geller [5]	Wh/mi, MPG	Modelica	20%
Simpson [34]	Energy (Wh/km)	PAMVEC	10%
Delorme [18]	L/100km (2008 to 2045)	PSAT	25%
Sharer [48]	Wh/mi Elec, Wh/mi Gas	PSAT	8%, 13%

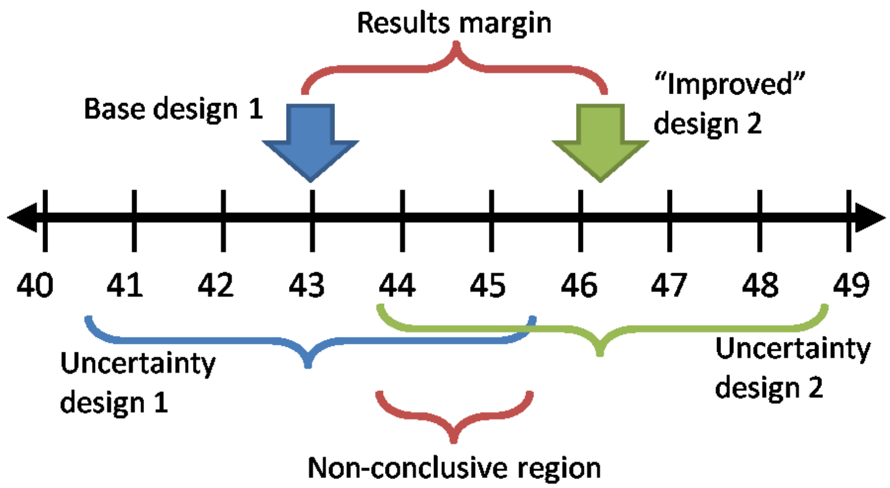

Figure 34 Evaluation of vehicle design improvement results margins and uncertainty for a design metric (ex. MPG).

One issue that arises in some of the simulation validation is the fine tuning of systems to get the desired results (fuel economy, acceleration, etc.). For example, controller parameters may be optimized so that a vehicle model with a simple controller produces results closely matching test data, when in fact the actual vehicle control system is likely to be much more complex. Although the tuning of the system may work well for a single case, it is not necessarily representative of real vehicle operation. For example, Cao [57] presents validations methods for PSAT using a PHEV converted Toyota Prius. The standard PSAT PHEV Prius model has 9% error for fuel consumption (L/100km) for CD operation, but with fine tuning of control strategy the error is reduced. The limited nature of the test case control tuning may lead to increased errors in other facets of the simulation such as different drive cycles.

Compounding uncertainty exists as design processes build upon one another. Uncertainty present in different portions of the simulation is combined together and is likely to culminate in amplification of result uncertainty. This effect increasingly promotes proper understanding of the uncertainty included in the simulations used to perform vehicle studies. A graphic representation of the uncertainty propagation through a simulation study is provided in Figure 35. Propagation of uncertainty in complex vehicle models can only be determined directly from the models being used. Some combinations of uncertainty can lead to increases in result uncertainty. By limiting the sources of uncertainty that are introduced to a study, the overall results uncertainty can also be controlled.

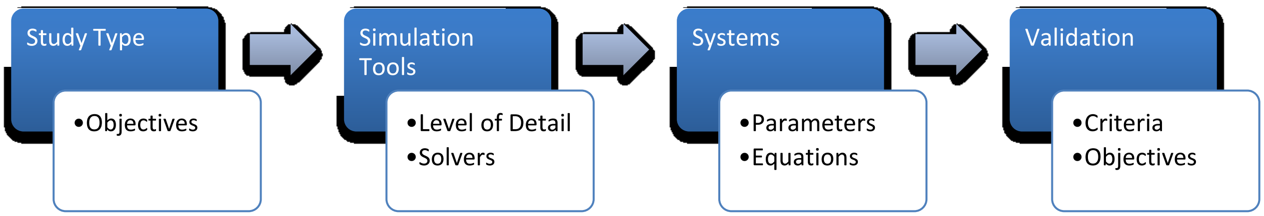

Figure 35 Representation of uncertainty propagation in vehicle simulation studies. Different portions of studies (blue squares) contribute different sources of uncertainty (white squares).

6.2.7 Discussion

By considering the sources of uncertainty in vehicle simulation studies we can understand more quantitatively the capabilities and weaknesses of vehicle simulation studies that have been performed. Investigation of previous vehicle design studies shows a lack of uncertainty consideration. Scientifically valid studies should include an accurate account of all information sources so that the uncertainty can be quantified. By including all of the uncertainty types presented in this paper (dynamics, numerical methods, parameter definition, assumptions/simplifications, and validation) future vehicle simulation studies can be improved. It is the job of the simulations tool developer to fully document the uncertainty that exists within their system, and the job of the researcher and simulation tool user to account for this uncertainty in conclusions that they develop.

One example of how the use of uncertainty consideration can improve a simulation study (other than just providing defensibility) is in simulation optimization. One of the major factors in performing an optimization is determination of convergence criteria. If the objective function metric has predetermined uncertainty, then the progression of the optimization should be considered converged when the difference between current iteration and the optimal answer are within the uncertainty range. Fellini [20] uses ADVISOR to optimize fuel economy, as an example, and should have set the optimization convergence criteria to be 5% (to be consistent with validation error and uncertainty). Accurate determination of the convergence criteria will affect the iterations necessary to complete the optimization and may even have changed the solution if the convergence criterion was set too broad.

Based on the information compiled through the development of this paper, the sources of uncertainty in vehicle simulation can be ranked according to their influence on uncertainty (% error). Figure 36 shows each of the five sources of uncertainty ranked from greatest to least influence. The ranking of the uncertainty sources is not definitive as each source has a probability of being either high or low depending on how they are applied. For example, even through Assumptions and Simplifications are ranked as contributing relatively high uncertainty, a researcher could develop highly detailed models that include few assumptions. The order of influence proposed incorporates finding based on literature and investigations from available sources as an average uncertainty found in each of the uncertainty sources.

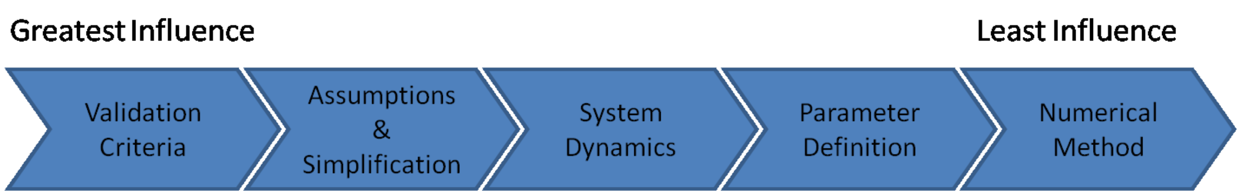

Figure 36 Ranking of influence for sources of uncertainty in vehicle simulations.

6.2.8 Summary of Uncertainty Quantification

As demand for vehicle simulation increases in both academic and professional areas, so does the requirement for accuracy within the simulations. To improve the accuracy of these vehicle simulations, researchers must account for uncertainty. Uncertainty can come from a wide range of sources throughout the simulation study process beginning at the determination of the type of study being performed and progressing through the evaluation of the study results. This paper quantifies the different types of uncertainty that exists within state of the art vehicle simulation studies and identifies areas that are important for future studies to consider. An extensive literature review has been performed and the combined conclusions of numerous sources have been integrated with author viewpoints to develop and broaden understanding of uncertainty in vehicle simulation studies.

6.3 Task 2.3 Characterize Drive Cycles as CONOP for Vehicle Simulations

System design tools including simulation and component optimization are an increasingly important component of the vehicle design process, placing more emphasis on early stages of design to reduce redesign and enable more robust design. This study focuses on the energy use and power management simulations used in vehicle design and optimization. Vehicle performance is most often evaluated in simulation, physical testing, and certification using drive cycle cases (also known as dynamometer schedules or drive schedules). In vehicle optimization studies, the information included in each drive cycle has been shown to influence the attributes of the optimized vehicle, and including more drive cycles in simulation optimizations has been shown to improve the robustness of the optimized design. This paper aims to quantitatively understand the effect of drive cycles on optimization in vehicle design and to specify drive cycles that can lead to robust vehicle design with minimal simulation. Two investigations are performed in service of this objective; Investigation 1 tests how different combinations of drive cycles affect optimized vehicle performance and design variables; Investigation 2 evaluates the use of stochastic drive cycles for improving the robustness of vehicle designs without adding computational cost to the design and optimization process.

6.3.1 Introduction to Drive Cycles as CONOP

Researchers commonly use dynamometer driving schedules as Concept of Operation (CONOP) for evaluating vehicle designs [58]. These driving schedules intend to characterize real-world driving and are the basis of tests used to measure the energy consumption of vehicles [59]. Driving schedules have been selected and standardized over time to provide a prediction of real-world operation, and to convey information on fueling costs, energy use, and emissions. The design, test, and calibration procedures used by major automotive manufacturers incorporate additional requirements beyond performance on commonly used drive cycles [34].

Vehicle system designers have difficulty in determining which driving schedules to consider in vehicle simulation and design processes [60, 61, 62, 63]. Many published design studies limit their scope by limiting the CONOP for vehicles to one or two driving cycles [34, 53, 62, 64 - 82]. Optimizing components and vehicle-level performance over this limited set of driving cycles can lead to less robust designs [54, 17], but increasing the number of cycles over which the vehicle will be evaluated adds to the simulation and design effort. This becomes especially relevant when optimization is introduced into the design process, commonly requiring significantly more simulation iterations [6, 83, 84].

The objectives of vehicle simulation research in literature range from detailed case studies to large-scale design space explorations [67, 71, 72]. Incorporating optimization into vehicle simulation studies has been shown to enable more rigorous comparison of vehicle designs within what is often a multimodal, nonlinear design space [58, 85, 86]. Previous work has shown that the characteristics of optimized simulated vehicles can change depending on the drive cycle considered [6]. Methods for simulation and optimization need to be developed that can provide robust and near-optimal vehicle designs while reducing computational costs.

To increase the robustness of the simulation and optimization paradigm for vehicle design studies, this paper analyzes the role of driving schedules in these studies. We present background information about the drive cycles, simulation tools and optimization methods used to conduct two experimental investigations. Investigation 1 compares the results of vehicle simulation and optimization for six standard drive cycles. The objectives of Investigation 1 are to determine how many drive cycles should be used to carry out a robust and defensible simulation optimization design study, and to analyze the dependency of optimized vehicle fuel economy (FE) and design variables on the drive cycles over which vehicle operation is optimized.

Investigation 2 evaluates the use of stochastic drive cycles derived from the information available in standard drive cycles. The discussion section describes that using Markov Chain drive cycles for simulation and optimization studies provides robust vehicle designs at reduced computational costs. The paper concludes that vehicle design studies that include simulation and optimization should incorporate stochastic drive cycles to improve robustness and reduce computational costs.

6.3.2 Background for Drive Cycle Characterization

The following sections describe the selection of drive cycles used throughout this study, simulation tools, optimization algorithm formulation, and the vehicle model.

6.3.2.1 Standard Drive Cycles

Vehicle simulation studies commonly use pre-defined drive cycles so that results are reproducible and comparable to laboratory tests. These drive cycles are most often formulated as time-series of vehicle velocity objectives. As a system-level CONOP for many design studies, the drive cycle selected for simulation can have a strong influence on the observed performance of the vehicle and on the characteristics of the resulting vehicle design.

Of 33 reviewed studies [34, 53, 62, 64 - 82], the most commonly used drive cycles (in order from highest to lowest frequency) were Urban Dynamometer Driving Schedule (UDDS), Federal Highway Driving Schedule (FHDS), Aggressive Supplemental Federal Test Procedure (US06), New European Driving Cycle (NEDC), New York City Cycle (NYCC), and the Air Conditioning Supplemental Federal Test Procedure (SC03) [87]. Other cycles, such as the Unified Driving Schedule (LA92), Japanese 10.15, and custom cycles were used at lower frequencies. The observed frequencies of the cycles used in the surveyed simulation studies are shown in Figure 37. These 6 cycles are the chosen for further investigation in this study.

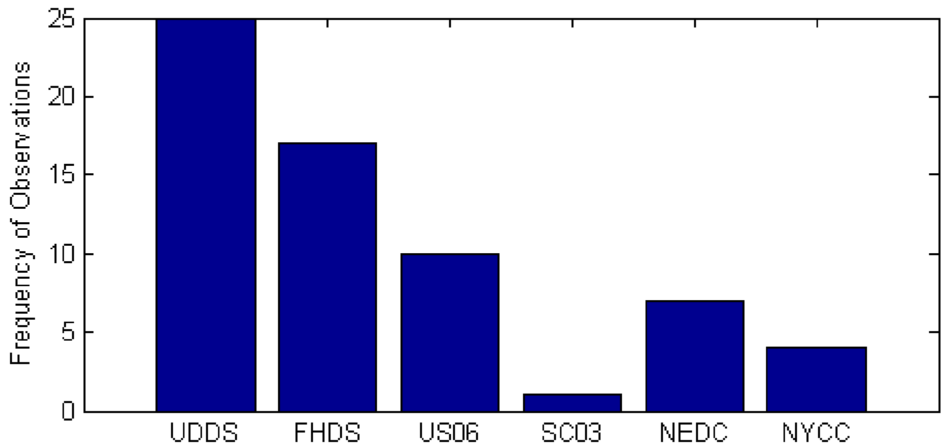

Figure 37 Frequency of drive cycle observations in simulation studies.

Many of these drive cycles are popular for vehicle simulation because of their association with vehicle FE and emissions regulation policies. The UDDS and FHDS make up the US Environmental Protection Agency's (EPA) test procedure prior to 2007. The US EPA presently uses a 5-cycle test procedure to evaluate all production vehicles. The 5-cycle procedure includes the UDDS, FHDS, US06 and SC03 cycles and a cold weather version of the UDDS test. The NEDC cycle is used by the Economic Commission for Europe (ECE) Dynamometer Operating

Cycles for regulation of vehicle construction and is comprised of four repeated ECE-15 cycles followed by an Extra-Urban driving cycle (EUDC).

The duration, distances, Characteristic Acceleration, Aerodynamic Speed, and Kinetic Intensity [88] of each of the six cycles used in this study are presented in Table 13[4]. Each drive cycle represents different types of driving behavior with a wide range of these cycle characteristics available among the 6 cycles.

Table 13 Characteristics of commonly used drive cycles

		UDDS (1)	**FHDS (2)**	**US06 (3)**	**SC03 (4)**	**NEDC (5)**	**NYCC (6)**	**Max: Min Ratio**
Duration	(Sec)	1880	764	600	600	1180	600	3.1:1
Distance	(km)	17.8	16.5	12.9	5.7	10.93	1.9	9.6:1
Characteristic Acceleration	(m/s2)	0.1764	0.0706	0.2104	0.2062	0.1122	0.3085	43:1
Aerodynamic Speed	(m/s)	14.81	22.75	27.75	15.26	19.08	7.76	3.6:1
Kinetic Intensity	(1/m)	0.8042	0.1365	0.2732	0.8850	0.3081	5.1259	37:1

Figure 38 shows the dominating data points for each of the six drive cycles observed in this study as well as average operating points. Similarities and differences between the cycles can be observed in Figure 38. The US06 cycle almost entirely dominates each of the other 5 cycles and has a higher average operating velocity than the UDDS, FHDS, SC03, and NYCC.

4 The UDDS is incorporated using the Federal Test Procedure (FTP) configuration which includes a complete UDDS (1375 seconds) followed by repeating the first 505 seconds of the UDDS.

The NYCC can be seen to have uniquely low average velocity, due to its high number of stop-and-go conditions.

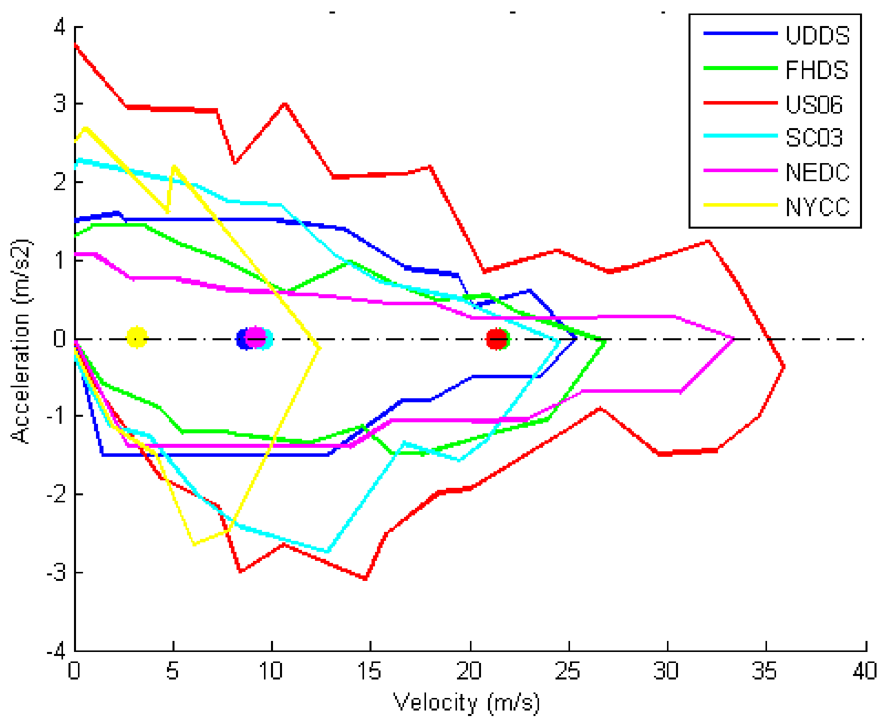

Figure 38 Acceleration and velocity ranges for six common drive cycles including complete-cycle averages. Lines represent bounding points while circles represent average data values for each cycle.

In summary, these six drive cycles exhibit a breadth of characteristics that will enable this study to understand the way that these drive cycles characteristics change the outcome of vehicle simulation and optimization studies. These six drive cycles will be used throughout the remainder of this study as basis for the development of vehicle simulation conditions.

6.3.2.2 Simulation and Optimization Tools

For this study, a custom Hybrid Electric Vehicle (HEV) simulation was constructed using the Modelica modeling language [89]. A set of 1500 nonlinear, time variant, Differential Algebraic Equations (DAEs) which represent the energy transfer, dynamics and control of a vehicle were solved using DASSL resulting in a low-cost, open source, object-oriented vehicle simulation toolbox. Verification and validation of the toolbox was performed through a comparison to conventional Matlab/Simulink simulation using ordinary differential equation solvers [6].

Pre- and post-processing of simulation data, as well as computation for the vehicle design optimization algorithm was performed in Matlab. A short amount of time is required at the beginning and end of each simulation to specify new design variables and then evaluate the performance of the vehicle from the result's data. The Simulated Annealing optimization algorithm was selected based on its ability to consistently identify optimized vehicle designs. The convergence limit for the optimization was set at 1000 iterations based on previous studies [6].

Vehicle designs were constructed as Hybrid Electric Vehicles (HEV) with a charge-sustaining vehicle energy management strategy. Optimization was performed using the cost function in Equation 5. SOC_{End} represents the final state of charge (SOC) of the vehicle at the end of a drive cycle, and SOC_{Bottom} represents the lower SOC control point. Vehicles start each drive cycle test with an initial SOC equal to SOC_{Bottom}.

Equation 5

$$\text{Minimize:}\left\{Fuel\ Consumption + SOC_{Penalty} + Cycle\ Deviation_{Penalty} + Acceleration_{Penalty}\right\}$$

Equation 6

$$Fuel\ Consumption = \frac{C}{\Sigma(\frac{d_i}{g_i})}$$

Equation 7

$$SOC_{Penalty} = \begin{cases} SOC_{End} \geq SOC_{Bottom} & 0 \\ SOC_{End} < SOC_{Bottom} & 10{,}000 \times (\sum SOC_{Bottom} - \sum SOC_{End} + 0.1) \end{cases}$$

Equation 8

$$Cycle\ Deviation_{Penalty} = \begin{cases} Cycle\ Deviation \leq 500m & 0 \\ Cycle\ Deviation > 500m & 100{,}000 \end{cases}$$

Equation 9

$$Acceleration_{Penalty} = \begin{Bmatrix} Acceleration_{\ 0-60mph} \leq \ 14\,s & 0 \\ Acceleration_{\ 0-60mph} \ > \ 14\,s & 100{,}000 \times (Acceleration_{\ 0-60mph} + 1.0) \end{Bmatrix}$$

Calculation of composite fuel consumption was based on Equation 6, where *C* represents the number of cycles included in the present optimization, d_i and g_i represent the distance (meters) and fuel consumed (grams of gasoline) over each cycle i, respectively[5]. Penalty was applied to the cost function for state of charge ($SOC_{Penalty}$) via Equation 7 for each simulated cycle if $SOC_{End} < SOC_{Bottom}$ (where SOC ∈ [0, 1]). $SOC_{Penalty}$ is normalized to the cost function units by a factor of $g/(m \times SOC)$. If the *Cycle Deviation* exceeded 500 meters then the cost was set to 100,000 for each respective cycle i from Equation 8. . $Cycle\ Deviation_{Penalty}$ is normalized by $g/1$. Finally, if $Acceleration_{0\text{-}60mph}$ exceeded 14 seconds the penalty from Equation 5 became active, wherein $Acceleration_{Penalty}$ is normalized by $g/(m \times s)$ for the cost function. Normalizing factors have no weight associated with unit conversions; instead weights are applied within each of the four cost contributing factors. Weight values and constants in Equation 8 and Equation 9 are derived to separate penalties by an order of magnitude. In this way, importance is placed on 1) meeting minimum acceleration, 2) reducing cycle deviations, and 3) exhibiting CS operation. Improvements to fuel consumption (likely 1-3 significant figures) are only observed after a viable vehicle has been verified. When they occur, SOC derived penalties have a value with 4-5 significant figures, deviation derived penalties have a value with 6 significant figures, and acceleration derived penalties have a value with 7+ significant figures.

5 An exception is made for the UDDS and FHDS only optimization (cycle set C=2) where the EPA 55% UDDS and 45% FHDS fuel consumption weighting is applied instead of the equal weighting from Equation 2.

This formulation supports the minimization of fuel consumption over each individual driving cycle, rather than minimizing average fuel consumption over the set of drive cycles. The distributed distance-weighting of the drive cycles (Equation 6) forces the optimization algorithm to design vehicles that can sustain battery charge over all of the cycles included in the optimization set. Other optimization formations that combine cycles in a front-to-back manner allow for charge-increasing and charge-decreasing cycles, resulting in poor vehicle performance if a driver were to operate continuously in charge-decreasing- cycles (i.e. continuous highway driving). The formulation used in this study ensures optimal vehicle operation over all driving conditions included in each respective simulated cycle set.

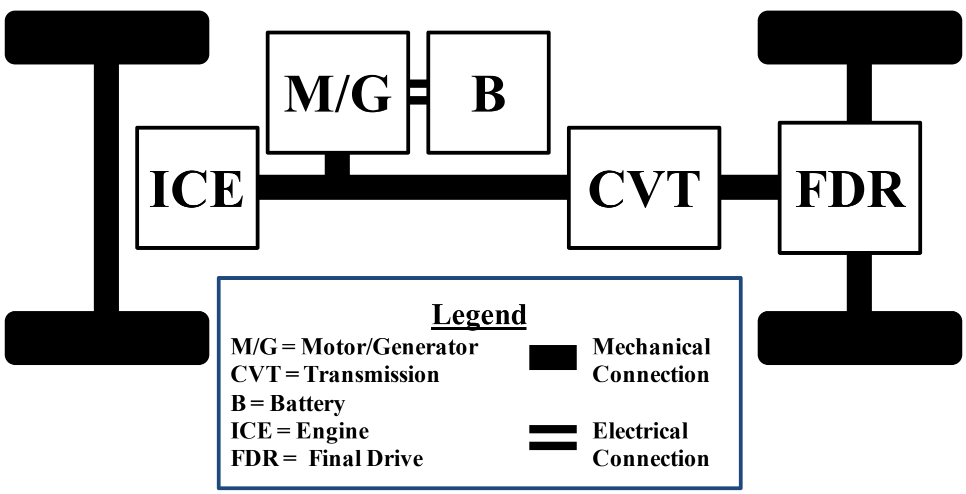

Figure 39 Pre-transmission parallel HEV.

The vehicle architecture used in this study is a pre-transmission parallel hybrid electric vehicle with a charge-sustaining battery management strategy. A diagram of the architecture is provided in Figure 39. This architecture was selected due to its high fuel consumption reduction potential as a Hybrid Electric Vehicle (HEV) and because this architecture has been considered in many other vehicle optimization and design studies [6, 58, 71, 79, 53]. The Internal Combustion Engine (ICE) uses gasoline as a fuel and is mechanically coupled to the

Motor/Generator (M/G) in a parallel configuration. Power flows between the ICE and M/G to the wheels via a Continuously Variable Transmission (CVT) and a Final Drive (FDR) differential. Mechanical connections are defined using conservation of both torque and angular velocity between components. Specifics of the model formulation have been described in previous work [6].

The vehicle model is comprised primarily of first principal equations governing conservation of energy as presented in many other research papers [65, 67, 70, 44, 49, 77, 78]. Energy management and control of the simulated vehicle is performed via logic similar to work by Rizzoni [63]. Driver requests are biased towards M/G use via Equation 10 which also allows for regenerative braking. $Torque_{MG\ Available}$ is calculated within the model based on state-dependent M/G and battery operating limits. Battery energy is managed in the parallel vehicle model using a thermostat-type control that follows closely to the ICE's Ideal Operating Line (IOL). Equation 11 describes how demands to the ICE are made based on the IOL, SOC, and driver request. $Torque_{IOL}$ is calculated using multiple functions that increase or decrease torque along the IOL based on SOC to keep battery charge within SOC_{Top} and SOC_{Bottom}. At low demand the ICE is allowed to turn off to reduce idle fuel use. Any power from the ICE in excess of driver request is regenerated by the M/G. Further specifics of the model formulation have been described in previous work [6].

Equation 10

$$Torque_{ICE\ Request} = Torque_{Drive\ Request} - Torque_{MG\ Available}$$

Equation 11

$$Torque_{ICE\ Demand} = \begin{Bmatrix} SOC \geq SOC_{Top} & Torque_{ICE\ Request} \\ SOC < SOC_{Top} & \max(Torque_{ICE\ Request}, Torque_{IOL}) \end{Bmatrix}$$

Design Variables (DV) are used as modifiable inputs for the vehicle optimization. Together, the DV determine the specifications of the components within the simulated vehicle. Building upon DV used in previous studies [83, 84], ten DV were selected for optimization of the pre-transmission parallel HEV. The names, short descriptions, and unit measurements for each of the DV are provided in Table 14. DV allow the optimization algorithm to scale both physical components and control aspects of the vehicle to find the most desirable vehicle design and control parameters.

Table 14 Optimization vehicle design variables with descriptions and units.

SOC Bottom (1)	SOC Top (2)	ICE T set (3)	MG T max (4)	FDR (5)	CVT R (6)	CVT O (7)	Batt P (8)	Batt E (9)	ICE T max (10)
Minimum SOC control target	Maximum SOC control target	Engine torque default for CS	Motor/ Generator maximum torque	Final Drive Ratio	Continuously Variable Transmission gear ratio scaling	Continuously Variable Transmission controlled input angular velocity limit	Battery Power rating	Battery Energy rating	Engine maximum torque
% DOD	% DOD	N*m	N*m	Ratio	Ratio	Rad/s	kW	kWh	N*m

The DV SOC Bottom, SOC Top, and CVT O are used as controller parameters within the model. These parameters define controlled operational limits of the hardware, and not the components of the vehicle. Although control strategy is an important aspect for improving vehicle operation, it will not be explored in this study. Numerous previous studies have investigated the gains achievable by advanced control strategies such as Dynamic Programming, Neural Networks, and stochastic control [76, 90, 93].

The remaining DV pertain to defining general hardware limitations. Uncertainty is known to exist when scaling component models. Specific efficiency relationships with hardware limitations and dynamic characteristics can vary across specific components. As an example, Battery P and Batter E approximate definitions of cell number and configuration for an energy storage system, but do not require a specific chemistry or cell characteristics. For simplicity, consistent scaling that relies on the DV are used for all models. More information on how the ten DV are used in models is available in previous work [6].

Simulation and optimization tools and methods have been presented as the foundation for performing the vehicle simulation studies. For this study, the UDDS, FHDS, US06, SC03, NEDC and NYCC drive cycles are used as CONOP for optimizing parallel HEV DV for FE and performance. Investigation 1 and Investigation 2 each present methods and results with the objective of advancing the state of the art in using drive cycles for vehicle simulation and optimization studies.

6.3.3 Investigation 1: Analysis of compounding standardized drive cycles

Investigation 1 aims to determine which of the standardized drive cycles are most desirable for integrated simulation and design optimization. Previous studies have performed limited investigations of optimizing on drive cycles, but not more than 1- and 2-cycle sets [84]. As additional drive cycles are included in optimization studies, information and constraints inherent in those cycles will become capabilities of the optimized vehicle design. Adding more test cycles to an optimization study thereby increases the robustness of the optimized vehicles, but at an increased computational cost. This investigation seeks to quantify this tradeoff between increasing the robustness of vehicle designs by adding drive cycles as additional CONOP, and minimizing simulation time by minimizing the number of drive cycles considered.

6.3.3.1 Methods for Investigation 1

The six drive cycles analyzed in the background section of this paper are to be used as CONOP in vehicle simulation and optimization. To perform the investigation, cycle sets are created that are composed of various numbers of these drive cycles. With this method, the first set of optimized vehicles was simulated using only the UDDS (1-cycle set). The second set of optimized vehicles was simulated on the UDDS and on the FHDS (2-cycle set). This process continued until the sixth set of optimized vehicles that was simulated on the UDDS, FHDS, US06, SC03, NEDC, and NYCC (6-cycle set).

Six independent optimizations to minimize fuel consumption were performed on each set of cycles. In total, over 150,000 drive cycles were simulated to provide data for Investigation 1, requiring over 2,500 CPU hours of simulation. All optimizations started with the same initial design point and different optimization algorithm random number seeds for consistency.

The objective function and penalties in Equation 5 through Equation 9 were used in the Simulated Annealing optimization algorithm. Less than 5% deviation in FE was observed for the final 100 iterations from each of the six design samples for each respective cycle set. The low variance in optimized design FE over the last 10% of the 1000 iterations supports the selection of convergence criteria used in this study [4].

6.3.3.2 Results for Investigation 1

The following results show the effects of compounding drive cycles on integrated vehicle simulation and optimization. Cycle sets are labeled according to the number of compounded cycles that are included in the optimizations, based on the order from Table 13. Six optimization design samples were performed on each of the drive cycle sets to provide statistically comparable data. The six cycle sets, each with six respective design samples, resulted in a total of 36 optimized vehicles. Computational costs increase with increasing simulated time as determined by the cycles included in each cycle set.

6.3.3.2.1 Optimized Vehicle Fuel Economy on the 6-Cycle sets

The optimized results for each of the cycle sets and optimization runs were analyzed based on FE (a scaled inverse of the cost function in Equation 5). Both the observed objective function FE and a City/Highway FE (C/H FE) mix (55% UDDS and 45% FHDS) were used for results comparisons. The C/H FE metric is included in this study so as to provide a consistent metric for evaluating vehicles as additional drive cycles are included in the optimization. The objective function metric used in Equation 5 changes the weighting applied to the simulated FE for each cycle to provide equivalent importance to each drive cycle. The objective function balances performance over all of the cycles included in the optimization so that the optimized vehicle will perform economically during all driving conditions. The mean and standard deviation for each of the cycle sets and each FE formulation are displayed in Figure 40. For both FE formulations the effects of using more than just the city and highway simulations in optimization can be observed.

As the number of cycles included in the optimization increase, from left to right in Figure 40, total average fuel economy for both the C/H FE and objective function formulations tend to decrease. The standard deviation of the samples also increases as the number of cycles increases, demonstrating increased variance of the optimized vehicle design as additional operating characteristics are applied to the vehicle's operation. Standard deviations increase from ~2% of the mean for the 1-cycle set to ~6% of the mean fuel economy for the 6-cycle set. The decrease in C/H FE with increasing cycle set number demonstrates that as the relative weighting of the UDDS and FHDS in the objective function decreases, the optimized vehicle designs show reduced performance on the C/H segments and an increased variance within the designs' C/H FE.

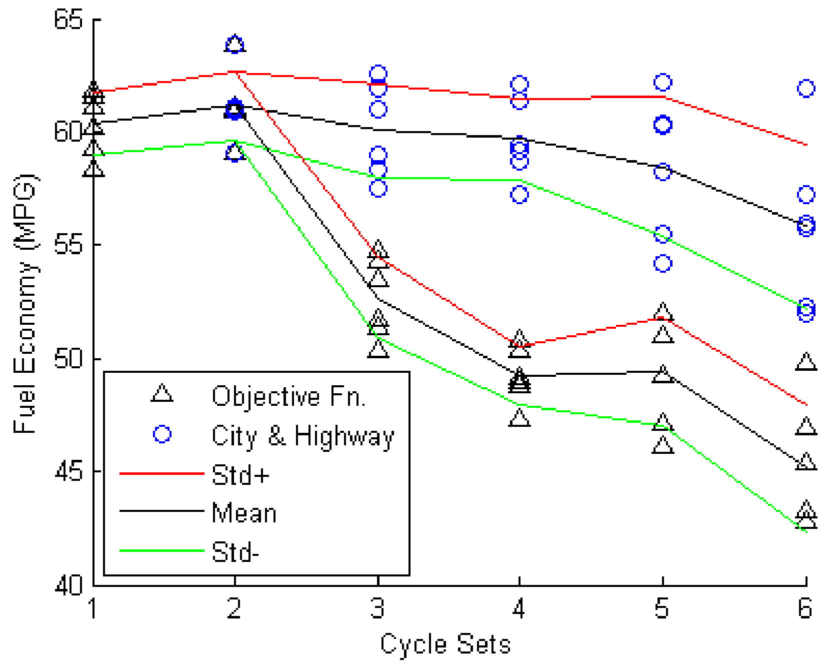

Figure 40 Simulation design optimization results showing optimized observations of fuel economy (mpg) for different increasing cycle inclusions. Observations shown for designed fuel economy over all included cycles based on the respective objective function and City/Highway formulation per cycle sets.

The first objective of Investigation 1 is to determine how many drive cycles should be used to carry out a robust and defensible simulation optimization design study. Figure 41 shows the Students' t test p-values when comparing all optimized vehicle performances using the C/H FE metric to the standard 2-cycle optimization set ("City/Highway", e.g. cycles 2&3, 2&4, 2&5, and 2&6). Also shown in Figure 41 are the p-values for a progressive comparison of the population of optimized vehicle fuel economy performances between cycle set n and cycle set n+1 ("Progressive", e.g. cycles 2&3, 3&4, 4&5, and 5&6). A high p-value between any two cycle sets would show a high confidence that the two optimized vehicle designs are not of significantly different populations (null hypothesis: difference of means is equal to zero).

As an example, a high p-value is shown between cycle sets three (US06) and four (SC03) for the progressive comparison method. This high p-value indicates that there is an insignificant change in simulated fuel economy between vehicles optimized over cycle set 3 (UDDS, FHDS, and US06) and vehicles optimized over cycle set 4 (UDDS, FHDS, US06 and SC03). In other words, the addition of the SC03 cycle does not significantly affect the FE results of the optimization when used in conjunction with the UDDS and FHDS. Similarly, the comparisons between C/H optimized FE and the FE of vehicles optimized over cycle sets 3, 4, and 5 shows that there are small but not negligible differences between the FE of vehicles optimized over many cycle sets and those optimized over only the C/H cycles. The addition of the NEDC (cycle five) is the only set that shows increased similarity to the C/H 2-cycle set, all other cycle additions decrease p-value C/H FE. This effect supports similarities found between the NEDC, UDDS, and FHDS cycles in previous studies [84].

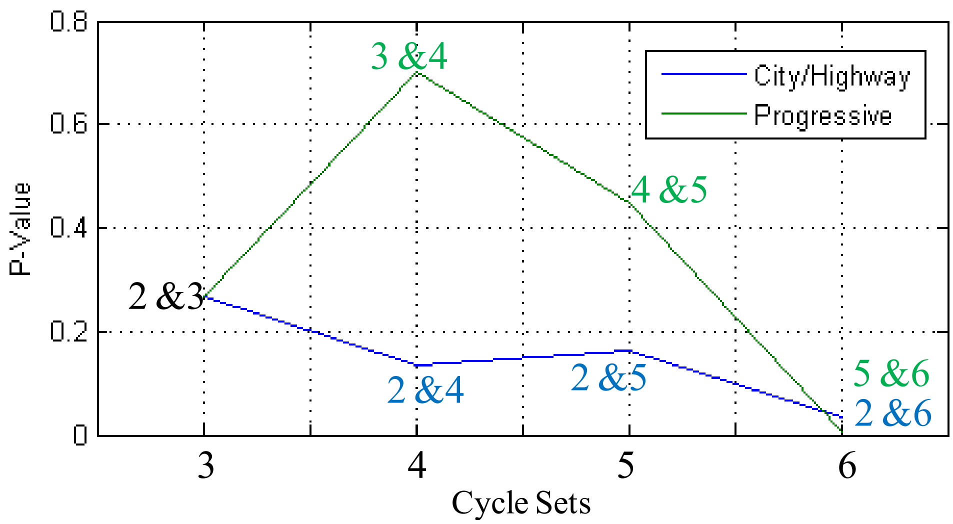

Figure 41 P-value of data set comparisons for FE between optimized design sets. All values based on C/H fuel economy comparisons. The City/Highway p-values compare each cycle set with the 2-cycle set, "Progressive" p-values compare between adjacent cycle sets.

The results presented in Figure 40 and Figure 41 demonstrate that the fuel economy of vehicles optimized over the first 2 cycles are statistically distinguishable from the fuel economy of vehicles optimized over six cycles when FE is compared using a C/H FE metric. To display the effect that additional drive cycles have on the overall FE of the optimized vehicle, Figure 42 shows the average FE for each drive cycle over each optimization cycle set. Figure 42 demonstrates that additional cycles progressively reduce the mean fuel economy achievable on each cycle, creating a spiral towards lower fuel economy as the number of cycles considered as CONOP increases. The scale of the FE reduction for increasing cycle sets is on the order of ~10% of the highest observed FE.

Decreasing FEs over compounding drive cycles should not be perceived as inferior vehicle designs. Instead, vehicles optimized over the broad range of conditions included in the 6-cycle set exhibit state of charge algorithms that are more robust to various driving conditions. For instance, vehicles that were optimized on the 1-cycle and 2-cycle sets were incapable of maintaining SOC on some of the other cycles. Figure 40 and Figure 42 serve to quantify this tradeoff between vehicle robustness and fuel economy performance.

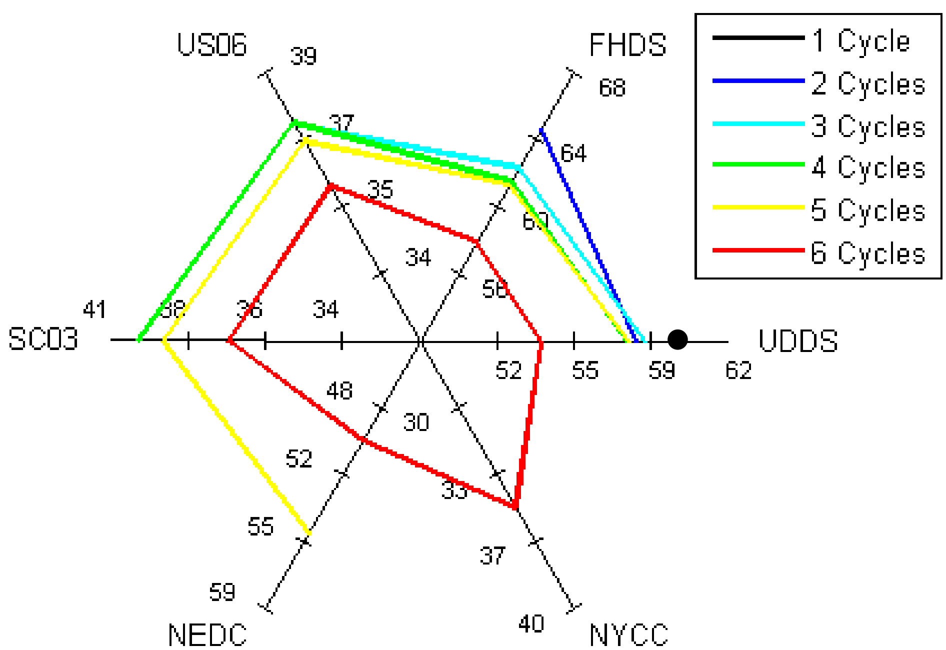

Figure 42 Radial plot of mean fuel economy on each cycle, separated by the number of cycles included in the optimization run.

In summary, the results of Investigation 1 show that if the only vehicle performance metric of interest is C/H FE, vehicle optimization studies will find no significant benefit from optimizing over more than the UDDS and FHDS cycles (2-cycle set). On the other hand, if the objective of the vehicle design study includes the development of vehicle designs whose fuel economy is robust to various driving conditions, optimization over more cycles can result in significantly different fuel economy than optimization over fewer cycles.

6.3.3.2.2 Optimized Vehicle Design Variables on the 6-Cycle sets

Systems engineering-based vehicle design studies often incorporate decision variables based on more than just the vehicle FE [53, 58, 18, 80]. Design considerations such as manufacturing costs, total cost of ownership (TCO), and manufacturability are dependent on the components used to construct the vehicle. The sizes and specification of these components are controlled in vehicle simulation and optimization studies through the set of DV. Based on results present in Section 3.2.1, we have demonstrated that more robust vehicle designs can be created by optimizing vehicle performance over more drive cycles. In this section, we compare the DV among vehicles optimized over different drive cycle sets to understand the role of the DV in determining robust FE performance.

The DV of the optimized vehicles are presented in Figure 43 to demonstrate the vehicle-subsystem effects of multi-cycle optimization. The 10 optimized DV shown in Figure 43 are presented as normalized values within each DV's observed range. Each variable is plotted for all cycle sets with the mean and standard deviation. The p-value for the cycle set in comparison with the 2-cycle set is shown to accentuate design deviations (associated with low p-values) from the standard C/H optimized vehicle.

We can identify from Figure 43 that some of the optimization drive cycle sets have DV similar to the C/H 2-cycle set while others are much different. Some of the DV, such as final drive ratio (FDR), change very little as the number of cycles in the sets increases (indicated quantitatively by high p-value across cycle set comparisons). The optimized values of DV such as peak motor torque (MG T max) and engine peak torque (ICE T max vary depending on the drive cycles over which the vehicle FE is optimized.

More generally, these results show that vehicle design studies which would like to consider metrics of performance that are related to the value of the DV (i.e. manufacturing cost, or TCO) must choose the cycle sets over which the vehicle will be optimized with care. The optimized values of the DV are strong functions of the number and types of cycles considered for optimization.

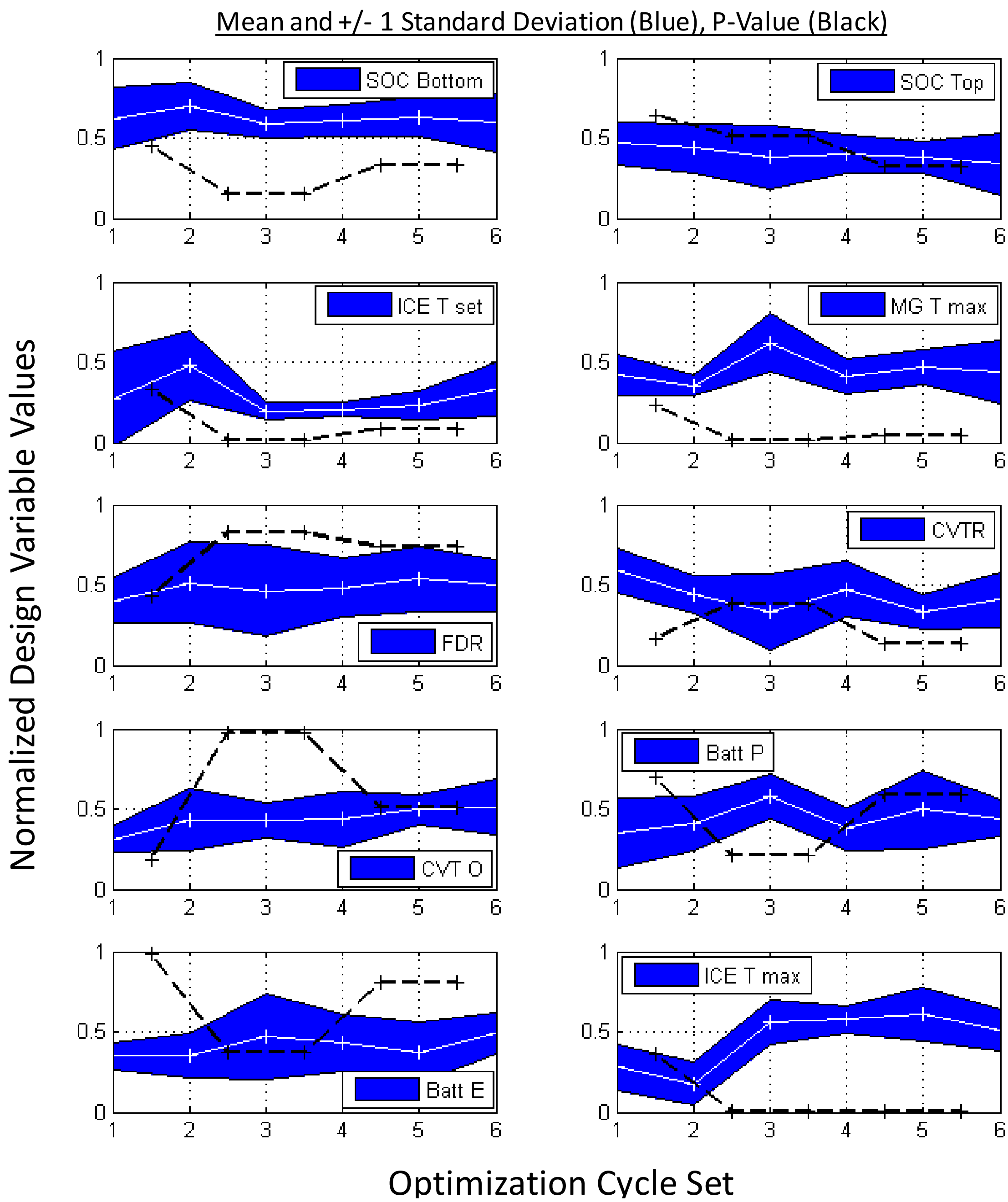

Figure 43 Optimized vehicle design variables for each of the optimized cycle sets. Crosses represent mean values and range expresses +/-1 one standard deviation from the mean. Values are normalized to the searched design space range. P-values are relative to the 2-cycle C/H optimized designs (e.g. comparison of cycle set 1&2, 2&3, 2&4, 2&5, 2&6).

Investigation 1 has analyzed and quantified the dependence of optimized vehicle FE performance and DV values on the number and type of drive cycles applied as CONOP to a vehicle simulation and optimization design study. Results show that studies focused on FE, particularly for city and highway performance, will see little change as additional drive cycles are incorporated. Studies only interested in city and highway FE should optimize vehicles over only the UDDS, FHDS, and the US06 cycles. These recommendations confirm those of previous work by Wipke et al [84] while providing additional breadth of drive cycle sets and depth of analysis. In contrast, vehicle design studies that would like to include system-level criteria that might be dependent on vehicle DV have a higher sensitivity to the cycle sets chosen for optimization. Including additional drive cycles as CONOP in vehicle simulation and optimization studies has more effect on vehicle design than on vehicle performance and will incur additional computational costs. To effectively model the design of robust vehicles, all drive cycles that represent expected driving conditions should be used in simulation and optimization.

6.3.4 Investigation 2: Analysis of non-standard drive cycles

The outcome of Investigation 1 confirms that the results of vehicle simulation and optimization studies are dependent on the drive cycles used as CONOP and that higher computational costs will be necessary for the design of vehicle to broader FE and design objectives. Investigation 2 aims to show whether vehicles optimized over condensed, stochastic drive cycles can replicate the vehicle design and performance results from the more computationally expensive 6-cycle set optimization at lower computational costs.

Stochastic drive cycles are hypothesized to offer two distinct advantages: 1) reduce the simulation time required to obtain optimized vehicles and 2) eliminate event-specific vehicle design optimization.

Although each of the 6 drive cycles studied in Investigation 1 has different cycle-average characteristics, there are events across cycles that closely relate to one another. By combining the information of events from all six drive cycles it is possible to create custom non-standard cycles that convey the same information to the simulation and optimization process using fewer data points, and therefore at a reduced computational cost.

Using standardized drive cycles in simulation optimization studies can result in unintended over-optimization for specific drive cycle events. This over-optimization occurs when a specified vehicle has been designed to operate ideally for the specific order of conditions that exist in a cycle. An example of this is when HEV battery packs are optimized to have just enough power to meet the high demand portion of the UDDS or just enough energy to charge deplete until the deceleration and regenerative braking section at the end of the FHDS. When vehicles are over-optimized in this manner, it can result in undesirable reduced performance when the vehicle is operated on other cycles or in real-world situations. To reduce the issues associated with the use of common drive cycles, stochastically determined cycles may be able to generate unique driving schedules each time the vehicle is simulated without changing the fundamental dynamics of the cycles.

6.3.4.1 Methods for Investigation 2

Markov Chains were selected as the method for generating statistically representative stochastic data series based on the results of previous vehicle studies [60, 90]. Markov Chains are defined as a collection of random variables having the property that, given the present, the future is conditionally independent of the past [91]. For vehicle driving applications, Markov Chains can be created by statistically observing occurrences of simultaneous acceleration and velocity in a progressive time series over the course of the standard drive cycle. To construct a drive cycle from these observations, the current state of acceleration and velocity can be used to provide the probability of a subsequent state. By incorporating each of the continuous time-series states for all six of the drive cycles into the Markov Chain transitional probability matrix, stochastic drive cycles can be generated [60, 90].

6.3.4.1.1 Markov Cycle Production

A transitional probability matrix was developed based on the information available in all of the six drive cycles used in Investigation 1. To create the matrix, an algorithm steps through each of the driving cycles and tallies occurrences of states in a multi-dimensional matrix as shown in Equation 12. *P_count* is the matrix of occurrence tallies, and *P* is the transitional probability matrix, as shown in Equation 13 such that *max(P) < = 1*. The *cumsum* of *P_count* is calculated by continuously summing tally values in a manner similar to English reading; left to right, top to bottom. In this manner *P(row = 1,col =1) = min(P)* and *P(row = N,col = M) = max(P)*. The index *k* identifies the time step of the cycle under observation. Using the Markov Chain methodology, *k* and *k*-1 are continuously mapped to *present* and *previous* states, respectively. At each time step in the cycle, the tally matrix *P_count* is updated, *P* can be updated after all cycle data has been obtained.

Equation 12

$$P\_count_{a_k,v_k|a_{k-1},v_{k-1}} = P\_count_{a_k,v_k|a_{k-1},v_{k-1}} + 1$$

Equation 13

$$P_{a_{k-1},v_{k-1}} = \frac{cumsum(\,P_{count_{a_{k-1},v_{k-1}}})}{\sum P_{count_{a_{k-1},v_{k-1}}}}$$

P_count and *P*, both *N* by *M* matrices, exist as cells in a larger *N* by *M* matrix where *N* and *M* describe the length of the velocity vector *v* and acceleration vector *a*, respectively. Vectors *v* and *a* are calculated based on the observable range of data for vehicle top speed and maximum/minimum acceleration capabilities, respectably. All of the observed drive cycles have an observed minimum velocity of 0 m/s and otherwise operate in the forward direction. As an example, the velocity vector v for the US06 cycle could be 0:0.1:36 because the top speed observed on the US06 cycle is 35.89 m/s. In this manner, probabilities of transition can be accessed by indexing the super-matrix stricture and locating the cell matrix of likely transitional states as shown in Figure 44. It should be noted that transitional probability matrices can be created based on any set of velocity and acceleration time-series data, allowing for stochastic cycles that are representative of any drive cycle. For this investigation, an observed-to-stochastic probability ratio of $2.5\text{x}10^8$: 1 was used, providing a very low probability that any unobserved states would spontaneously occur.

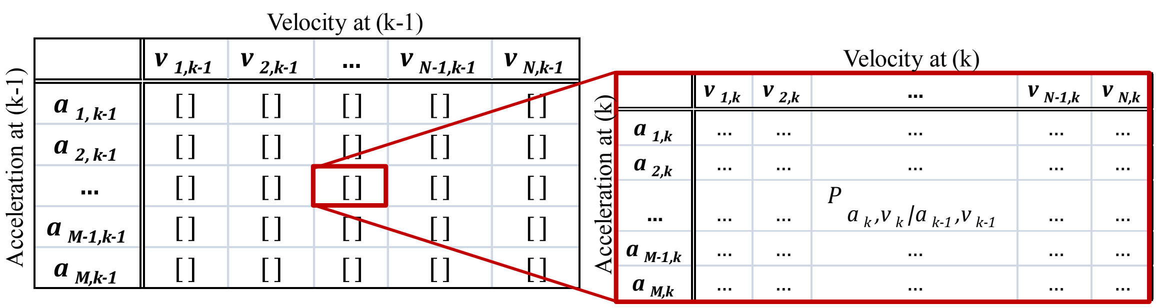

Figure 44 Structural representation of transitional probability matrices.

After the matrix structure P was updated with the information present in the six standard drive cycles used in this study, stochastic number generators were used to create new representative cycles from Equation 14. X represents a uniformly generated random number [0-1]. Based on the present vehicle acceleration and velocity state in the generated cycle, the transitional probability matrix can be used to determine a subsequent state. All of the cycles created for this study begin with an initial resting state: zero velocity and zero acceleration.

Post-processing of the created drive cycle data set ensures that extreme combinations of acceleration and velocity as well as negative velocities do not occur.[6]

Equation 14

$$[a_{k+1}, v_{k+1}] = location[\ \min(P_{a_{k+1},v_{k+1}|a_k,v_k} - X_{k+1}) \geq 0]$$

For this study, drive cycles were created for a given duration rather than for a given distance. This formulation was chosen so that an equal number of time-series events are used in all cycles. With this method there is no guarantee that the cycles will end with a stopped vehicle, which is not common in conventional driving schedules but is entirely acceptable for simulation studies.

A distance-specific weighting was applied to the occurrence of events within each incorporated cycle to provide a closer approximation of the cycle weightings used in the 6-cycle set objective function. Shorter cycles were allocated a proportional increase in significance by multiplying the occurrence of states in the Markov Chain observations from Equation 6. This method approximates the observation of cycle-specific states that would occur if all cycles were of equivalent distance and thus equivalent importance in the objective function. The method of weighting importance of drive cycles is extensible to approximate any other cycle weightings desired by vehicle designers.

6.3.4.1.2 Implementing Stochastic Cycles

Implementing stochastically created drive cycles generates a problem not observed when using standardized cycles. With stochastic cycles, a probability exists of creating drive cycles with relatively "easier" or "harder" characteristics. Inconsistent cycles result in an inconsistent

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6 Comparing Equation 7 and 8 shows that the transitional probability matrix shifts from [k-1 and k] to [k and k+1], respectively as the method changes from creating the matrix based on observations to using the matrix to predict new cycles.

evaluation of different vehicle designs. For example, a poor design may exhibit the same FE on an "easier" cycle as a better design would on a different "harder" cycle. To understand what makes up these characteristics of drive cycles, they have been characterized by O'Keefe [88] using three metrics: characteristic acceleration, aerodynamic velocity, and their dependent Kinetic Intensity (KI). KI is calculated as a ratio of characteristic acceleration to aerodynamic velocity. Kinetic Intensity is identified as the defensible metric to quantify the intensity of a driving profile and is shown to have a positive correlation with fuel consumption in vehicles. Variability in power and energy demands between simulations was reduced by selecting Markov-Cycles with KI equal to that of the combined six cycles (±0.01 1/m).

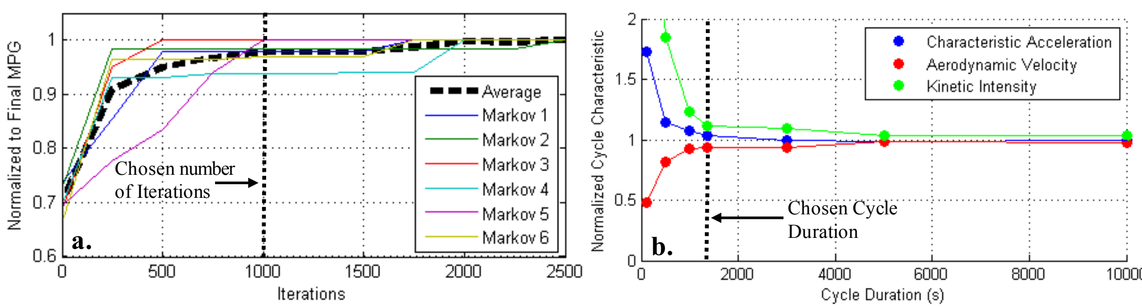

Figure 45 Convergence criteria for Markov cycles. Normalized FE vs. optimization iterations (a) and cycle characteristics vs. cycle duration (seconds) (b).

Various convergence criteria were investigated to ensure appropriate implementation of the Markov Chain stochastic cycles. Figure 45 shows the convergence considerations: iterations in optimization (a) and cycle duration (b). These convergence criteria were selected due to their importance in satisfying the interests of the investigation. The achieved optimized FE as a function of iteration number is shown in Figure 45 (a). The average optimization exceeded 90% of the final optimized value in fewer than 500 iterations; all except one of the six optimizations exceeded 95% of the optimized FE in 1000 iterations. Comparing 1,000-iteration and 2,500-iteration Markov-Cycle optimized designs, a maximum difference of 1.05 MPG was found. The 1,000-iteration and 2,500-iteration optimized vehicles had an average FE difference of 0.3 MPG and a p-value of 0.82. The highest optimized DV difference between 1,000-iterations and 2,500-iterations is DV-3 (ICE T set) with 11% change in mean DV value. Average change is 2.87% between 1,000-iteration and 2,500-iteration DV. As a result of these considerations, 1,000 iterations were selected for the Markov-Cycle optimizations.

As has been demonstrated by other studies, Markov drive cycles exhibit the characteristics of the original cycles [60]. Figure 45 (b) shows the progression of median characteristic acceleration, aerodynamic velocity, and kinetic intensity for 100 Markov cycles, as a function of Markov-Cycle duration. Values in Figure 45 (b) are normalized based on the characteristics of the composite 6-cycle set test. As the Markov-Cycle duration approaches the duration of the composite 6-cycle set, their characteristics converge. The diminishing returns on cycle characteristics for increasing simulated time can be seen for simulations greater than ~1000 seconds in duration. As an approximation of this return, Markov-Cycle duration of 1880 seconds was selected, matching the duration of the UDDS. This allows for a Markov drive cycle implementation that retains a majority of the characteristics of the originally investigated 6 cycles while reducing the total simulated (and thus computational) time relative to the 6 cycle set.

Before each and every simulation performed in Investigation 2, a new unique Markov cycle is generated. Computational time required to generate each Markov cycle is minor when compared with computational time for each simulation ($\sim 1x10^6$:1 simulation-to-generation computational time ratio). This approach results in no two iteration's cycle having identical profiles, but the characteristics of all cycles are closely matched.

6.3.4.2 Results for Investigation 2

The objective of Investigation 2 is to show that these stochastically created cycles can accurately approximate the 6-cycle set's characteristics and optimized vehicle design results with reduced computational costs. Using the Markov cycles with transitional states based on the distance-weighted 6 cycles, six independent vehicle design optimizations were performed. Each iteration of the optimizations simulated a uniquely generated Markov cycle. Optimized vehicle FE performance and resulting vehicle design variables were evaluated for each optimization study.

6.3.4.2.1 Optimized Vehicle Fuel Economy on Markov cycles

The first objective of Investigation 2 is to demonstrate that the Markov-Cycle optimized vehicles have the same characteristics and performance as vehicles optimized over the entire 6-cycle set. To form this comparison, Investigation 2 measures and analyzes 4 metrics of characteristics and performance 1) weighted C/H FE, 2) FE over each drive cycle, 3) dynamic powertrain function, and 4) robustness to drive cycle starting point.

To demonstrate the performance of Markov-Cycles, the first comparison is between each cycle set's optimized FE with the Markov-Cycle optimized FE. The highest correlation for both C/H and composite objective function FE derivations appears with the 6-cycle set optimized vehicles at $p=0.69$ for C/H and $p=0.81$ for the objective function (inverse of Equation 1). The high p-value for the six optimized vehicle design's FE indicates that the Markov-Cycle optimized vehicles are highly similar to the 6-cycle set optimized vehicles in terms of composite FE performance.

To further investigate the performance of the Markov-Cycle optimized vehicles, Figure 46 compares the FE of the vehicles optimized over the 6-cycle set and the vehicles optimized over the Markov-Cycles on the basis of their FE over each of the six independent drive cycles. The FE performance matches closely indicating that the Markov-Cycles are robust surrogate CONOP models for the 6 drive cycles. The UDDS and FHDS cycles have the largest differences between the 6-cycle set and Markov-Cycle optimized vehicle performance, but each difference is less than 2.8 MPG (<5%). When compared with Figure 42, Figure 46 demonstrates that the FE for all six of the drive cycles is most closely matched by the Markov-Cycle optimization than any other cycle set. Figure 46 shows that Markov-Cycle optimized vehicles retain the cycle-specific FE of the 6-cycle set optimized vehicles.

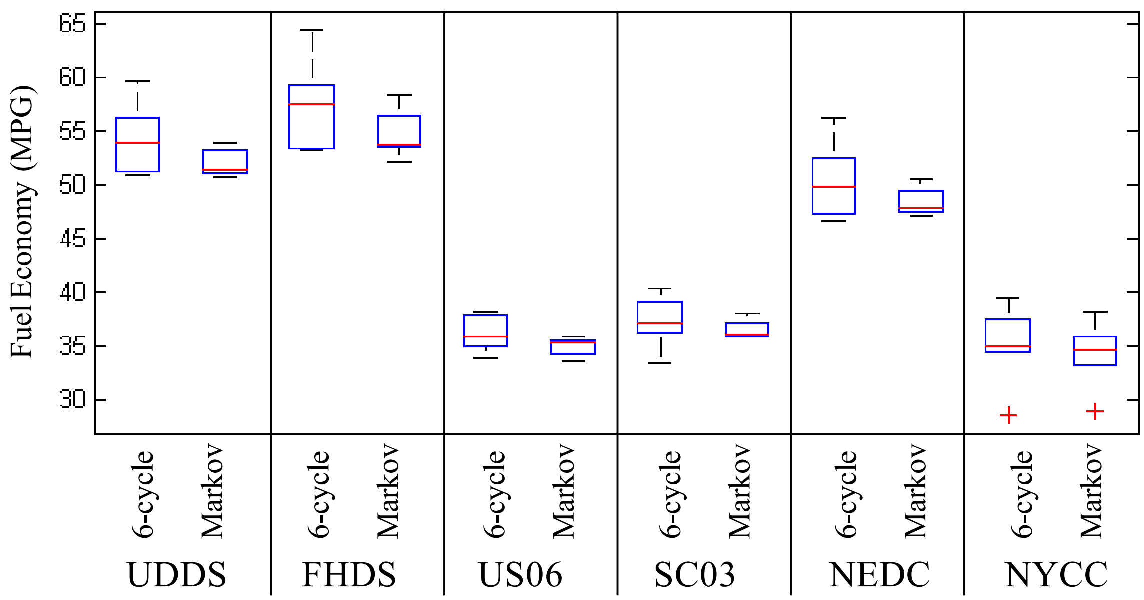

Figure 46 Box plot of FE on each drive cycle for the 6-cycle set and Markov optimizations. Median, 25th and 75th percentiles, data range and outliers are represented.

The operational characteristics of the vehicles optimized using different cycle sets is shown in Figure 47 where the engine torque and battery SOC are plotted for vehicles over the duration of the UDDS. The Markov cycle optimized vehicle's operation is more closely related to the vehicle optimized on 6 cycles, than it is to the operation of the vehicle optimized on a single UDDS cycle. It can also be seen that the Markov and 6-cycle vehicles' engine operates in a load-following manner as evidenced by the small changes in battery SOC that occur over the drive cycle. This can be contrasted to the steady-state operation of the engine in the optimized 1-cycle vehicle, as evidenced by the larger changes in battery SOC and smaller changes in engine torque over the duration of the drive cycle. It is likely that the load-following control strategy is what allows the Markov and 6-cycle optimized vehicles to perform more robustly under different driving conditions.

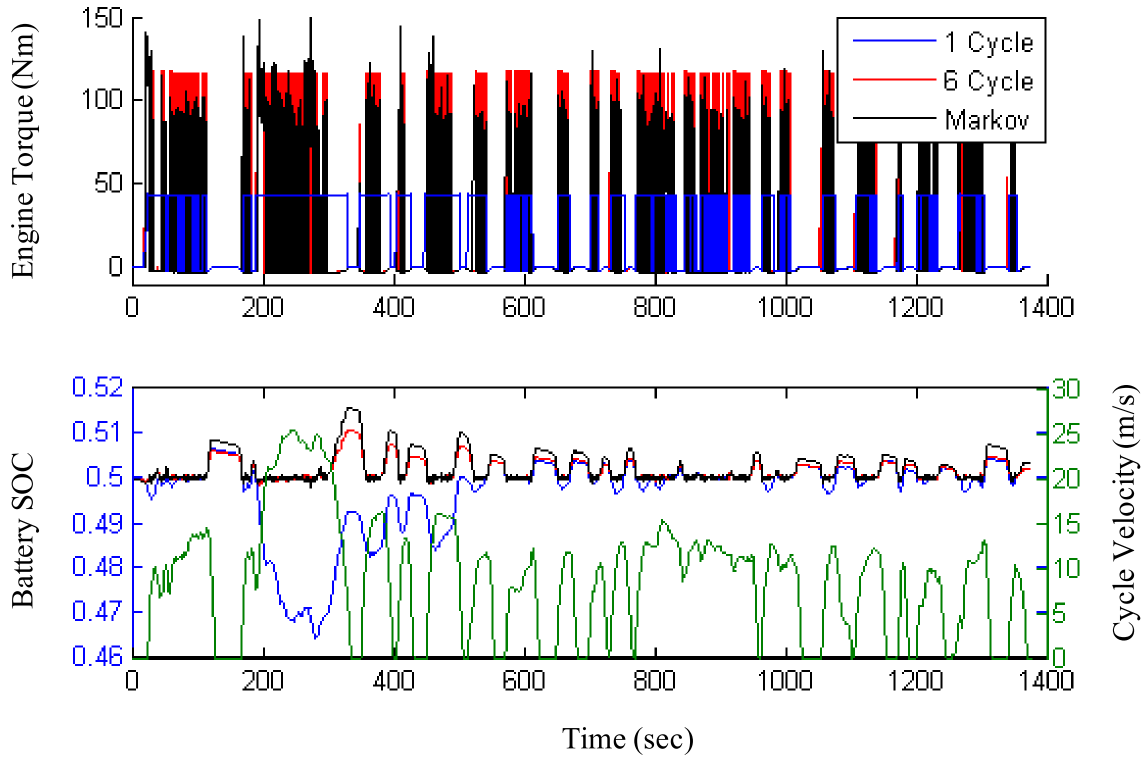

Figure 47 Overlay of engine torque and battery state of charge over the UDDS for vehicles optimized over 1 cycle, 6 cycles, and using Markov cycles.

6.3.4.2.2 Evaluation of Robustness

A vehicle's ultimate ability can be quantified by the extent of different states that it can successfully operate in. For this purpose, a state is defined based on the Markov-Chain formulation of four conditions: present and preceding acceleration and velocity. Increasing cycle sets has the potential to increase observed states that can be optimized for. While controls modification can ensure a vehicle reaches all of its hardware-limited states, expansion into additional states requires increasing component specifications. Higher cycle sets have more states than lower cycle sets. Vehicles optimized for multiple cycles include the requirements to perform in simulation over these additional state conditions.

Vehicle design robustness can be achieved through a combination of hardware selection and control method development. As described in Investigation 1, vehicles optimized for fewer cycle sets (1-cycle set and 2-cycle set) have optimized power (ICE, MG and Battery) specifications lower than higher cycle sets and were unable to complete cycles beyond those optimized on. It is reasonable to assume that the control method implemented in this study is too simple to allow the vehicles to exhibit their ultimate ability. Vehicle-specific control method improvement may prove to allow additional optimized vehicles to complete all 6 cycles. This study uses a consistent control method across all optimized vehicles and shifts the focus for robustness to hardware-based limitations. As vehicles optimized on the Markov and 6-cycle set include the most required states, they offer the highest potential for hardware-based robustness.

Vehicles optimized on the 3-cycle set and above all exhibited the ability to complete all 6 cycles. To additionally test the robustness of the vehicle designs, each of the optimized vehicles was simulated over the 6-cycle set starting at points in the cycle different than the standard starting point. Using the same cycles but starting at different starting points (each simulated vehicle started at the same new point for each cycle for consistency) retains all of the information present within the cycle but demonstrates the sensitivity of optimized vehicle designs to end-of-cycle boundary conditions. All of the six Markov and six 6-cycle set optimized vehicles were able to maintain SOC on all but one of the cycles while the 3-cycle set optimized vehicles had four failures (of 6 samples) due to low SOC. All of the Markov, 6-cycle set, and 3-cycle set vehicles were able to maintain SOC on all six cycles when simulated from the standard cycle starting points. This ability demonstrates that the robustness of performance and controllability that the 6-cycle optimized vehicles are able to achieve is maintained through the use of condensed cycles.

These comparisons demonstrate that the FE performance, control system function, and robustness characteristics of the Markov-Cycle optimized vehicles are indistinguishable from those of the 6-cycle optimized vehicles.

6.3.4.2.3 Optimized Vehicle Design Variables on Markov cycles

Although the FE of Markov-Cycle optimized vehicles is comparable to the FE of 6-cycle set optimized vehicles, the results of Investigation 1 have shown that the value of DV can be sensitive to optimization CONOP. The DV for the optimized Markov-Cycle vehicles must show a correlation with the optimized 6-cycle vehicles to demonstrate equivalent utility between the two approaches.

Comparison of the ten design variables used in this study show that high p-values are observed between the optimized Markov vehicles and the 6-cycle set optimized vehicle designs. To demonstrate the correlation of DV, Figure 48 shows DV statistics for both Markov-Cycle optimized vehicles and 6-cycle set optimized vehicles. Nine of the ten DV for the 6-cycle set optimized vehicles have less than 10% difference with the Markov-Cycle optimized vehicles. All of the DV of Markov-Cycle optimized vehicles have p-value correlations with the DV of 6-cycle set optimized vehicles above 0.1, eight of which are above 0.2. The average p-value between Markov-Cycle optimized designs and 6-cycle set optimized designs is 0.49.

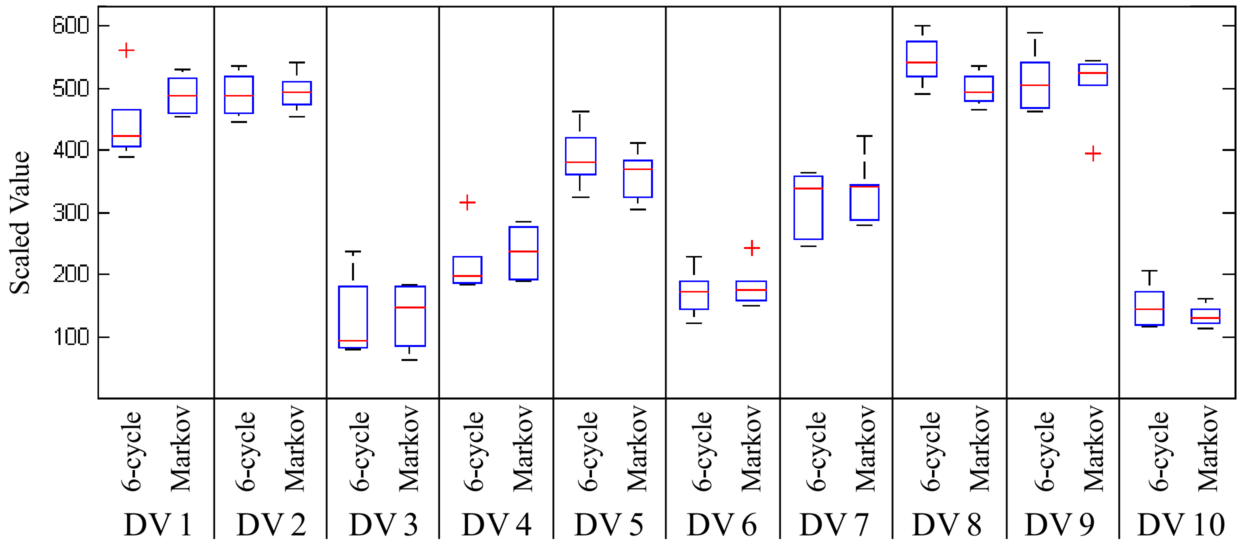

Figure 48 Comparison of design variables between Markov-Cycle and 6-cycle set optimized vehicles using box plots. Median, 25th and 75th percentiles, data range and outliers are represented.

6.3.4.2.4 Computational Advantages

The Markov-Cycle optimization completed ~2.8x faster for this study than the complete 6-cycle set optimization with comparable results. The average computation time required for each cycle's simulation is provided in Table 15. To assist in understanding why it is possible to reduce the computation time using Markov Cycles, Table 15 also provides the number of discrete acceleration vs. velocity states observed in each cycle. When Table 15 is compared with the duration of each cycle in Table 13, it can be seen that all cycles have reoccurring states and also that reoccurring states exist across different cycles. Over 50% of the states observed for the 6-cycle set are repetitions. Using the Markov-Cycles provides statistically similar state occurrences in a reduced simulation time.

Table 15 Distinct states and observed computation time for each of the drive cycles investigated.

	UDDS	FHDS	US06	SC03	NEDC	NYCC	6-cycle	Markov
Distinct States	856	320	503	427	189	369	2427	2427[7]
Computation Time (Seconds)	519	242	176	163	336	132	1567	563

Observing all of the DV and performance metrics surveyed for this study, the Markov-Cycle optimized vehicles show a high level of similarity with the 6-cycle set optimized vehicles, producing robust vehicle designs with less computational cost.

6.3.5 Discussion

To date, many HEV design studies have optimized vehicle simulations using a limited set of drive cycles [34, 53, 62, 64 - 82]. Investigations 1 and 2 of this paper have shown that the energy-use performance and optimized vehicle components used in these designs are highly dependent on the cycle-sets used as CONOP in each study. Vehicle design processes using fewer drive cycles produce vehicles designs that are less robust to diverse driving characteristics. Stochastic drive cycles offer the robustness of using multiple cycles in vehicle simulation optimization and with lower computational costs.

To aid in the application of the simulation and optimization tools presented in this paper, the assumptions and limitations applied when investigating standardized and condensed drive cycles as CONOP are discussed here. Uncertainty within the study and additional application considerations are offered.

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7 Presents number of available states. Due to stochastic state selection, actual number of observed states per cycle may be lower.

6.3.5.1 *Uncertainty, Variability and Error*

Many state of the art vehicle design studies do not appropriately document the uncertainty, variability, and error associated with their design efforts. This study has demonstrated that uncertainty exists in all aspects of vehicle simulation, optimization and comparison. To aid future researchers in understanding and trusting the results presented in this study, all analysis and comparisons have been fully documented and presented here including uncertainty. Consideration of this uncertainty brings to question the error, uncertainty, and statistical comparisons that are required to draw conclusions from vehicle design studies. Based on the results of this study, we can now understand the uncertainty that is associated with the results of vehicle simulation and optimization design studies. For this section p-values below 0.05 are considered significantly different (at a 95% confidence level, $\alpha = 0.05$) [59] assuming a normal distribution of values.

Typically, vehicle simulation tools observe uncertainty in calculated output (e.g. MPG or GHG emissions) from 5% to 20% [4]. An uncertainty of ~5% for FE has been measured for the simulation and optimization tools used in Investigations 1 and 2 [4]. Additionally, design variable definitions can have associated uncertainty ranging from 1% to 20% [44]. Both of these factors decrease the correlation required for acceptably accurate results and thus increase the validity of the methods proposed in this paper. The results of Investigation 1 show, in Figure 40, that increasing the number of cycles included in the optimization also increases the performance variability within each results set. Figure 49 shows the variability for each of the optimized cycle-sets FE presented as the proportion of the standard deviation to the mean. The Markov-Cycle variability for both the C/H and Cost Function quantifications are lower than the 6-cycle set and on par with 3-cycle and 4-cycle sets.

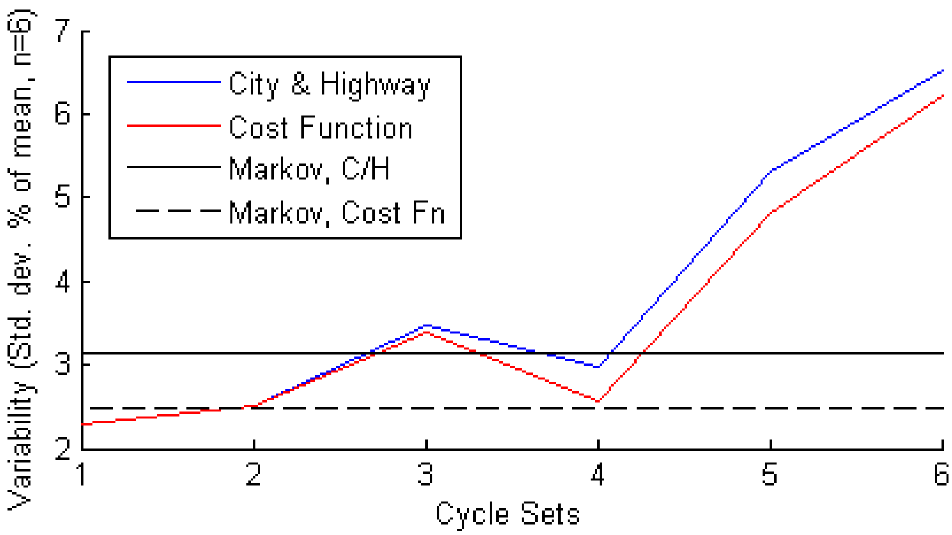

Figure 49 Relative measured uncertainty in optimized designs for a variety of FE metrics compared among the six cycle sets and Markov-Cycle optimized vehicles

Investigation 1 can now be reexamined to determine the accuracy of the conclusions. In Figure 41, the lowest p-value comparing cycle set's FE for the C/H formulation is between the 2-cycle set and 6-cycle set at 0.032, all others are higher than 0.10. Between progressive cycle sets, the 5-cycle set and 6-cycle set show the lowest p-value at 0.007, all others are above 0.25. These comparisons with high p-values do not support rejection of the null hypothesis, suggesting that (for instance) the mean FE for the 3-cycle-optimized vehicles is not different than the mean of the 2-cycle-optimized vehicles. Between the progressive cycle-sets, as the number of cycles included increases, only the 6-cycle set supports rejection of the null hypothesis, suggesting that 2-cycle-optimized and 6-cycle-optimized vehicles do not have the same mean FE. Using a 95% confidence interval, only two of the ten DV (DV 2 & DV 8) is significantly different between the Markov-Cycle and 6-cycle set optimizations. At a 99% confidence level ($\alpha = 0.01$), all design variable comparisons would fail to reject the null hypothesis, suggesting that these same DV comparisons are insignificantly different.

6.3.5.2 EPA and Standardized Testing

To show the extensibility of the condensed cycles used in Investigation 2, the FE results are applied using metric of comparison different than either the C/H FE or cost function FE. For example, an important FE metric is the EPA 5-Cycle weighted FE, used for vehicle sticker labeling [59]. Vehicle design performance was approximated using the proportional fuel consumption weightings for the Three-Bag FTP at 75°F found in the EPA documentation. Ambient temperature effects are not included in the vehicle model; therefore fuel consumption for cold-start portions of the test procedure are approximated using suggested EPA methods [59].

For this metric of comparison, the Markov-Cycle optimized vehicles perform most similarly to the 6-cycle set optimized vehicles, with p-values above 0.15. In contrast, the comparison between Markov-Cycle optimized vehicles and the 4-cycle set optimized vehicles FE has p-values below 0.01.

These comparisons show that the similarities between the stochastic drive cycle optimized vehicles, and the 6-cycle optimized vehicles exist not only for those metrics of comparison that are explicit inputs to the optimization routine, but also exists for metrics of comparison outside of the original objective function.

6.3.5.3 Comparison to Previous Studies

When vehicle simulation and optimization studies are used as inputs to a subsequent detailed vehicle design process, the fidelity with which the simulation and optimization tools can represent the performance of the vehicle is of high importance. Accurately approximation of vehicle attributes reduces the probability of redesign. To test the utility of using condensed Markov-Cycle simulation optimization, a comparison can be made with previous design study methods and a high volume production HEV, the Toyota Prius (MY2012). A study presented by

Gao et. al. [83] performed simulation optimization on pre-transmission parallel HEV. Within the Gao et. al. study, models and algorithms similar to those used in this paper were applied. As with many of the studies examined through the literature review, only the UDDS and FHDS drive cycles were used by Gao et. al. as CONOP. The vehicle attributes presented in Figure 50 are the ratio of ICE power to total tractive power (% ICE), total tractive power to weight ratio (kW/gram), and FE to weight ratio (MPG/gram). The weight ratios are included to minimize effects from assumptions made to model the chassis in each study. The HEV designed by Toyota (which likely included design and testing CONOP beyond the 2-cycle set) has attributes more similar to the optimized 6-cycle set and Markov-Cycle found in Investigations 1 and 2 than to the optimized Gao et. al. and 2-cycle set vehicles. This comparison demonstrates the relatively weak correlation that exists between the outputs of simulation and optimization-based design studies and real-world OEM vehicles, and suggests that including more drive cycles as CONOP (and the condensed Markov-Cycle versions) will allow design studies to more closely approximate real-world OEM design results.

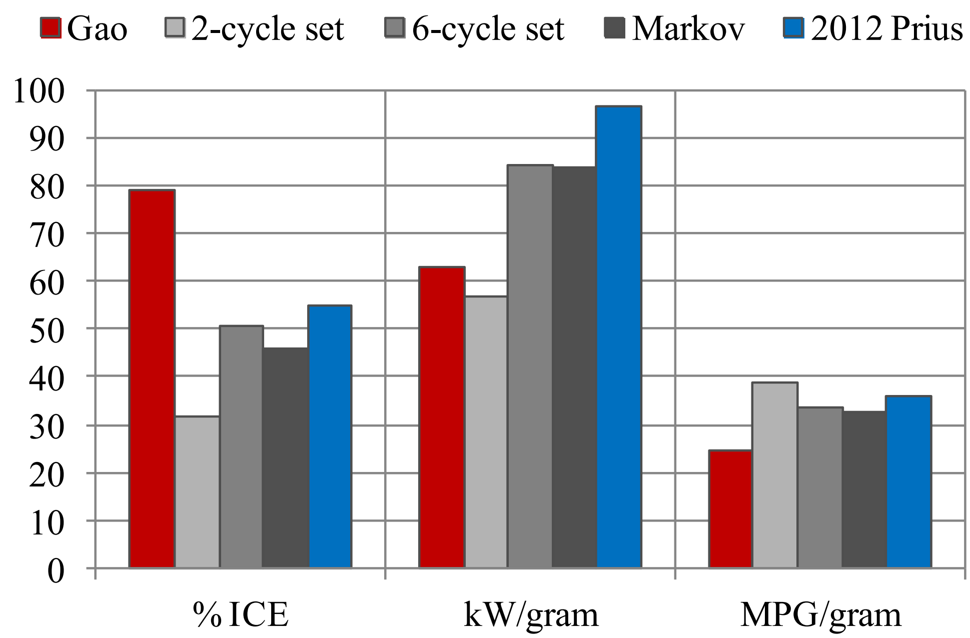

Figure 50 Comparison of optimized vehicle attributes.

6.3.6 Conclusions

The methods shown in Investigations 1 and 2 of this paper will assist automotive designers in determining appropriate drive cycles for simulation optimization. Investigation 1 systematically compared HEV designs optimized on the UDDS, FHDS, US06, SC03, NEDC, and NYCC standard dynamometer driving cycles. Results of Investigation 1 show that City (UDDS) and Highway (FHDS) rated FE does not change significantly when additional drive cycles are added to the optimization. In contrast, the vehicle design variables (and subsequent analyses dependent on their values) are highly dependent on the types of drive cycles used in the optimization. Investigation 1 shows that to design an optimized HEV capable of robust operation over a variety of different driving conditions, as many drive cycles as are available should be included in the vehicle design study.

Investigation 2 presented an alternative method of simulating drive cycles in a condensed manner and with reduced computational costs. The methods used in this paper also offer an additional advantage of reducing cycle-specific event dependence, allowing optimized HEV to operate more consistently in un-modeled or off-design driving conditions. The methods of Investigation 2 can be applied to any combination of drive cycles. The stochastically derived cycles, as shown in Investigation 2, can allow future vehicle design studies to improve the robustness of their optimized vehicles while simultaneously reducing the computational costs associated with the design process.

Overall, the use of simulation and optimization in vehicle design studies will improve the consistency, applicability and utility of simulation within the vehicle design process. By seeking to experimentally and empirically understand the dependency of vehicle design on the best practices in the simulation field, this study contributes to the improvement of both vehicle simulation efforts and their dependent conclusions.

6.4 Task 2.4 Determine the effect of fleet characteristics on vehicle simulation.

Automobiles have been classified into various groupings over the years to provide divisions for policy and consumer perspective. The present automotive classifications are not well suited to account for design and technology improvements over time. Restricting automotive classification to only a few metrics has forced agencies to update their classifications by including new groups as markets and fleets change. In the U.S., the Environmental Protection Agency (EPA) classifies passenger cars based on their passenger and luggage volume while trucks are classified based on their weight. To aid in restricting the scope of automotive studies, many researchers apply automotive classifications to provide distinction between different automobile types, while avoiding the comprehensive modeling of every vehicle make and model. Some policy, energy, and technology studies choose a single carline in their analysis [138] where other chose a carline per each vehicle class included [106, 115]. In many cases these studies fail to consider the representativeness of selected automobile carlines within its fleet. The choice of representative automobiles in fleet-level technology studies needs to be determined in terms of: similarity of the automobile's characteristics to others in the same group, applicability of the automobile's technology to others in the same group, and effectiveness of this automobile's technology to the group. In this study we are proposing a new automotive classification that groups automobiles with similar characteristics including a variety of engineering design parameters and fuel economy. These classifications will be intended for application to fleet-level automobile fuel economy studies. Based on the identified automobile groups, the most representative carline per each group will be selected and the measure of technology effectiveness on this automobile will be tested and compared to the overall group and entire U.S. fleet. The results of this study will improve the effort required to measure the affect and impact of technology and design improvement while simultaneously increasing the robustness of automotive classification over time.

6.4.1 Introduction

Automotive design studies are important to advancing the state of the field. To provide structure for understanding differences between automobiles, classification methods are used. The prevalent method of reliance on the existing automotive classification has a drawback. Historically most U.S. studies use EPA classifications[8] that rely on passenger/luggage volume and weight, but there is low correlation between these characteristics and metrics of interest to the vehicle design and simulation community, including Fuel Economy (FE). The correlation

8 "How are vehicle size and classes defined?" fueleconomy.gov

between EPA reported FE and combined passenger and luggage volume is shown to be low in Figure 51.

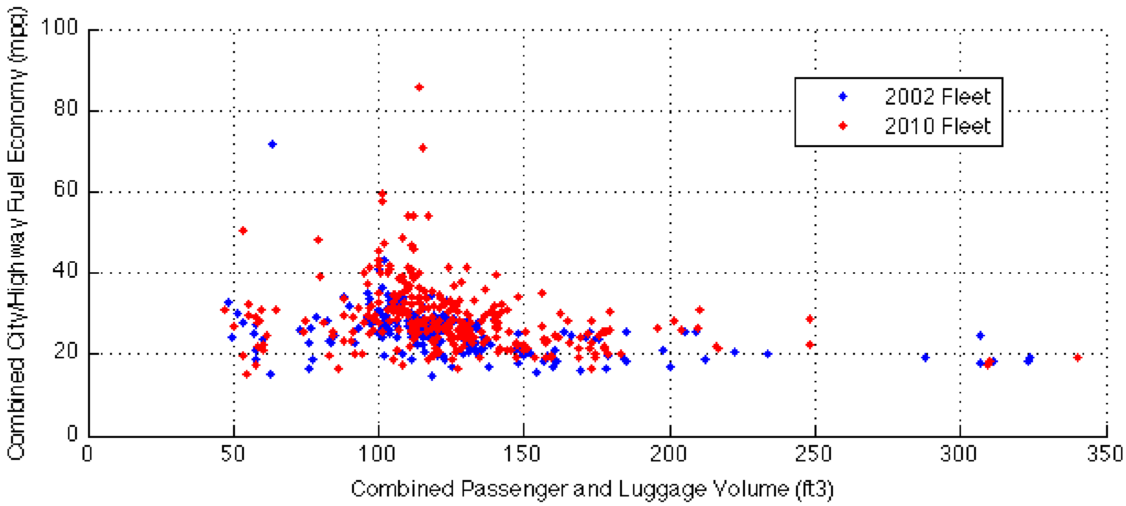

Figure 51 Low correlation between automotive interior volume and fuel economy.

The current classifications are designed for consumers or regulation where it is not meant to account for automobile design and technology improvement. Restricting classification to size and weight has forced agencies to update their classification by including new classes over time. There is a need to reclassify automobiles by using their significant characteristics to better represent the fleet in automotive design and simulation studies.

This paper proposes a new method of automotive classification based on clustering of technology characteristics. This approach aims to 1) improve the state of the art for automotive design studies on fuel economy, GHG emissions, and other energy-use scenarios by providing more relevant and representative vehicle classification, and 2) reduce scope of studies by exploring more efficient approaches to representative automobile identification.

6.4.2 Previous Fleet-Level Studies

In automotive design and analysis studies, researchers have either added to or subtracted from the EPA classifications in order to achieve their objectives for modeling of the vehicle fleet.

For example, a study by Austin and Dinan added additional automobile classes (luxury small, and luxury large) to the EPA classification system account for variability in fuel economy and MSRP. The luxury vehicles have higher prices at lower fuel economy than their mid-sized or full-sized class median counterparts [126].

In other automotive design studies, the researchers have chosen to delete many of the EPA classifications. For example, in a study by the Electric Power Research Institute (EPRI) a Saturn SL1 was selected as a compact vehicle, Ford Explorer as a mid-size SUV and Chevrolet Suburban as the full-size SUV [106]. In another study a Toyota Camry was adopted as the representative automobile for five different technologies [138]. Neither of these studies presented evidence that the model they chose was representative of the automobiles they were attempting to represent. Additionally, the applicability of each studied technology is unknown for the fleet because it is only simulated as applied to a single model. To provide more robust results, researchers need to understand whether the technology is applicable to more than one automobile category or not. Additionally, the representativeness of the selected model for other models in the fleet is unknown.

6.4.3 Methods

In this paper the authors propose a methodology for clustering the U.S. light duty automotive fleets based on available automotive characteristics. The analysis targets automobiles sold in U.S. for model years (MY) 2002 and 2010. The goal is to determine the minimum number of clustered automobile groups necessary to achieve certain metrics of representativeness of the fleet for each year. In addition, representative carlines will be identified for each cluster. Clustering approaches will be implemented using SAS while automobile modeling and simulation will occur in Modelica. Four clustering methods were tested and the one with best performance is promoted and used for discussion and analysis. The quality and performance of each step in the analysis (clustering method, number of clusters, and the choice of exemplar automobiles) is reviewed.

6.4.3.1 Database for U.S. Automotive Fleet Sales Characteristics

U.S. vehicle model year fleets of 2002 and 2010 will be considered in this analysis. These MY have been selected to demonstrate fleets across multiple years that show significant change in market and fleet characteristics. Example changes between MY 2002 and 2010 include the introduction of electrified transportation and the addition of new EPA classes.

The U.S. EPA reports the characteristics of vehicles for each nameplate such as tested dynamometer coefficients, fuel economy, passenger volume and luggage volume. Not every nameplate was tested by the EPA for each MY, for some nameplates neither its fuel economy nor volume data were reported. In addition, the sales data publically available from Autonews[9] is only accessible on a per-carline basis. These limitations lead the authors to carry the analysis over the carlines where each carline represents the median of the nameplates. Table 16 provides an overview of the data set that is used throughout this study.

Table 16 Database overview for MY 2002 and 2010 automobiles

	2002	2010
Total Fleet Sales	15,291,878	11,580,715
Nameplate EPA characteristics/ fuel economy	2,364/945	3,322/1,109
Carlines used in this analysis	190	304
EPA Classes	13	15

9 www.autonews.com

6.4.3.2 Proposed Automobile Classification Method

The proposed classification method is designed to support automotive studies related to energy, environment, market, and policy. The results will be automobile clusters that classify vehicles based on the vehicle level characteristics: Engine Power (HP), Number of Gears (Gears), Estimated Test Weight (ETW), Axle Ratio (Axle), Engine/Wheel Speed Ratio (NV), Fuel Economy (FE), dynamometer coefficients, passenger volume, and cargo volume.

The clustering analysis was carried out using all available automobile characteristics to allow for division of vehicles into groups (clusters) of automobiles that are homogenous within each cluster and heterogeneous among other clusters.

The steps for this analysis are as follow:

1. Obtain automobile sales data (nameplate) and respective characteristics for a specific model year (MY).
2. Carlines are identified by class, make and model name
3. Compose the mean value of each carline characteristics using automotive characteristics (HP, Gears, ETW, Axle, NV, THC, CO, CO2, NOx, TARGET_COEF_A, TARGET_COEF_B, TARGET_COEF_C, SET_COEF_A, SET_COEF_B, SET_COEF_C, FE_CTY_Unadjusted, FE_HWY_Unadjusted, Passenger_Volume, Luggage_Volume)
4. Calculate the mean of each model year (2002, 2010) fleet classes (using EPA classification)
5. The clustering and statistics analysis were coded in SAS (the sales number "frequency" for each carline has no effect on the clustering analysis, where carlines are grouped, or clusters the same way):

6. Normalize each automobile's characteristics
7. Select clustering procedure (Single, Complete, Average and Ward's)
8. Obtain a quality measures to decide on the number of clusters
9. Interpret and profile clusters
10. Define an exemplar carline within each cluster.

6.4.3.3 Clustering Method

Clustering is defined as assigning objects into groups (clusters) based on their similarity level of some criteria. Many clustering methods exist and can lead to different results based on their formulation. There are two type of clustering classes; Hierarchical and Non-hierarchical [127]. The Non-hierarchical approach requires many random starting runs since it is sensitive to initial starting condition where the hierarchical clustering approach can be run once for each data set. In the hierarchical clustering approach a tree structure (dendrogram) with k-blocks (k: number of clusters) is created [128]. The k-blocks set partition for each value of k between 1 and n, where n is the number of observations to be clustered based on the clustering method.

In this study, I have selected to use a Non-Parametric (Hierarchical) agglomerative approach. This works by building a hierarchy clusters using a bottom up approach. Each observation starts as a single cluster and then pair of clusters are merged based on their similarity level defined by the linkage method. The strengths with this approach are that any desired number of clusters can be obtained by cutting the dendrogram at the proper level.

In our analysis we tested the performance of four methods: Single, Complete, Average, and Ward's. Figure 52 lists the classification of each type. The following sections will provide an overview for each of the investigated clustering methods.

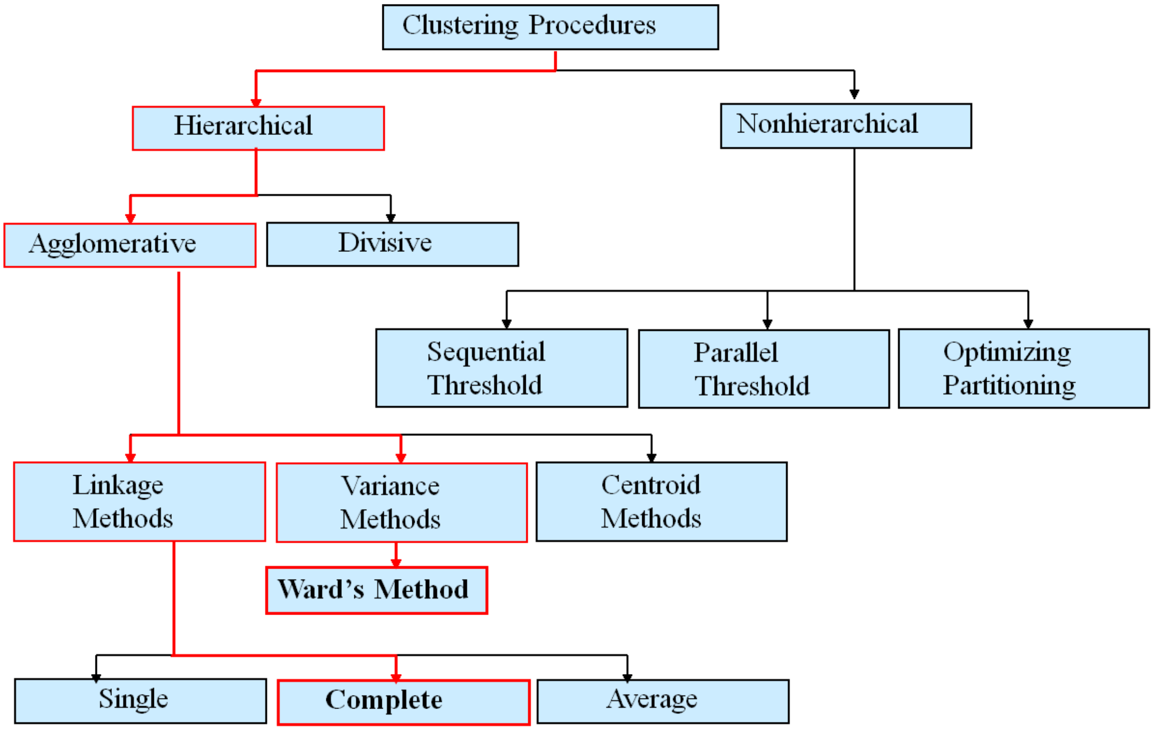

Figure 52 Classification of clustering types [Bernard and Downs 1992].

6.4.3.3.1 Single linkage method

The single linkage method [129] is defined by the minimum of all pair-wise distances between points in the two clusters. The dissimilarity between two clusters is equal to the minimum dissimilarity between the members of two clusters. The distance between clusters *R* and *Q* is shown in Equation 15.

Equation 15

$$d_{Single\ Linkage}(R,Q) = min\left(d_{i,j}\right), for\ i \in R, j \in Q$$

Where $d_{i,j}$ is the distance between the *i*th and *j*th observations. This method produces long, "loose" clusters and sensitive to noise and outliers. A graphical representation of the Single Linkage Method is shown in Figure 53.

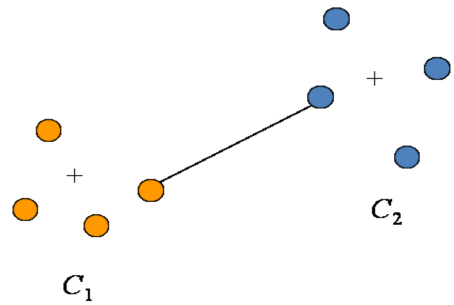

Figure 53 Single Linkage Method

6.4.3.3.2 Complete Linkage Method

The Complete linkage method [130] is defined by the maximum of all pair wise distances between points in the two clusters where the dissimilarity between two clusters equal to the maximum dissimilarity between the members of two clusters. The distance between clusters $\underline{R}$ and Q is shown in Equation 16.

Equation 16

$$d_{Complete\ Linkage}(R, Q) = max\left(d_{i,j}\right), for\ i \in R, j\ \in Q$$

This method is produces more balanced clusters (with equal diameter), less susceptible to noise and very tight clusters. A graphical representation of the Complete Linkage Method is shown in Figure 54.

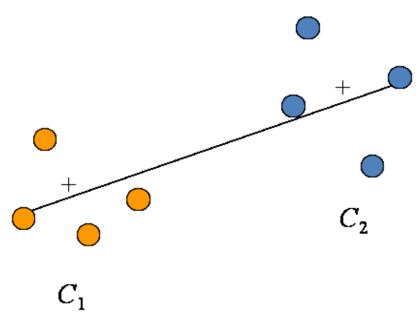

Figure 54 Complete Linkage Method.

6.4.3.3.3 Average Linkage Method

The Average linkage method [131] is defined as the average of all pair wise distances between points in the two clusters where the dissimilarity between two clusters equal to the averaged distances of all pairs of objects (one from each cluster). The distance between clusters R and Q is shown in Equation 17.

Equation 17

$$d_{Average\ Linkage}(R,Q) = \frac{\sum d_{i,j}}{|R||Q|}, for\ i \in R, j\ \in Q$$

Where $|R|$ and $|Q|$ equal the number of observations in cluster R and Q, respectively. This method compromise between Single and Complete Link and it is less susceptible to noise and outliers but biased towards globular clusters. A graphical representation of the Average Linkage Method is shown in Figure 55.

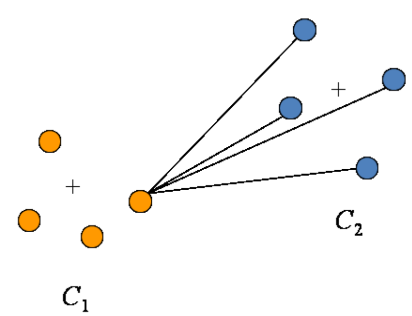

Figure 55 Average Linkage Method.

6.4.3.3.4 Ward's Method

The Ward's method [132] is defined by the difference between the total within-cluster sum of squares for two clusters separately, and the within cluster sum of squares (SSE) resulting from merging the two clusters. The error sum of squares is shown in Equation 18.

Equation 18

$$SSE = \sum_{i=1}^{K} \sum_{j=1}^{n_i} (y_{i,j} - \overline{y_{i,J}})^2$$

Where y_{ij} is the jth observation in the ith cluster and n_i is the number of observations in the ith cluster.

This method is similar to group average and centroid distance. As such, it is less susceptible to noise and outliers, is biased towards globular clusters, is a hierarchical analogue of k-means, and can be used to initialize *k*-means.

6.4.3.3.5 Clustering Method Selection

This study does not aim to make an exhaustive comparison between clustering methods but instead to choose the one with best performance as applied to the selected automotive data sets. The selection process is executed by applying each method to the data sets. The resulting clusters have been evaluated using the maximum distance between clusters, quality of grouping, grouped automobiles within each cluster, and the final median value of characteristics within each cluster. The objective of the cluster evaluation is to maximize the similarity within each cluster and minimize similarity between clusters.

6.4.3.4 Defining the Number of Clusters

The four methods (Single, Complete, Average and Ward's) were evaluated to choose the one with the best performance using the 2002 and 2010 MY automotive data. The most desirable clustering method has been identified as the method that produce high quality clusters with high within-cluster similarity and low between-clusters similarity. The methods and assumptions in regard to the number of clusters are tested to carry the analysis using the method with best performance.

The Semi-Partial R-squared (SPR) measures the loss of homogeneity when forming a new cluster from merging two clusters. The value is small when the merging clusters are homogeneous and large when they are not [133]. For example, applying the Ward's method shows that seven clusters are efficient because after the seventh cluster increasing the number of clusters will lead to a small maximum distance increase as seen in Figure 56. Ward's method joins clusters with a small number of observations, produces clusters that have with almost the same number of observations and very sensitive to outliers [137]. Based on the initial analysis the authors have chosen the Ward's method based on its desirable performance.

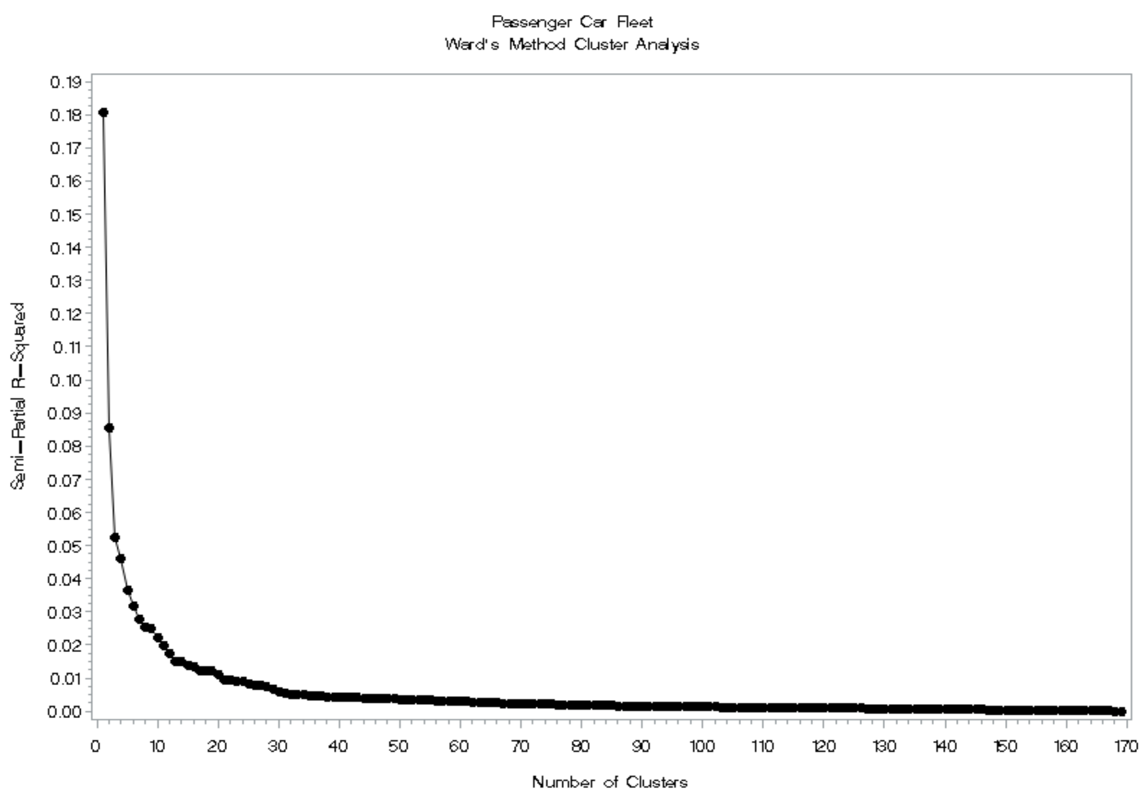

Figure 56 Maximum distance between clusters using the Ward's Methods with 2010 data.

6.4.3.5 Definition of the Exemplar Vehicle

Each cluster will represent a group of automobiles with a high level of similarity. A wide range of approaches exists for selecting exemplar automobiles within a group depending on the metric of interest. For example, if a researcher is focused on analyzing automotive acceleration and total power they may select exemplars based on median power rating for each cluster group. For this study, exemplar carlines are selected based on median sales volumes within each grouping. In this manner, the characteristics of each group (Clusters or EPA Classes) are preserved through segregation of the clusters, and the additional factor of sales weighting can then be added. Sales weighting is important to evaluation of the exemplar's automobile's ability to represent the entire U.S. fleet for a given year.

The exemplar methodology has an important feature that allow the representative carline from each cluster within each fleet to be used as an exemplar in technology, fuel economy, performance, and emission, energy, and policy studies. This has many advantages in regard to the computation time, costs and level accuracy in performing policy/energy modeling. Including sales volumes into the study will demonstrate the proposed methodology's ability to represent characteristics not included in the original analysis. Exemplar automobiles have been selected from each cluster using median sales volume data. The exemplar vehicle is the vehicle in each cluster with the highest sales volume, and is presented as the exemplar for the cluster for the remainder of this study.

6.4.3.6 Modeling and Simulation Methods

To test the performance of the clustering method for automotive classification a method is proposed as follows:

1. Models of the automobile fleet must be created that can accurately simulate FE performance based on automobile physical characteristics.
2. Incremental technology changes are made to the modeled vehicle fleet

3. Comparisons of the simulated change in FE can be made between the predicted EPA classified representative automobiles, cluster representative automobiles, and the fleet as a whole.
4. The best classification scheme is then the classification scheme that allows for the lowest mean error in prediction of the fleet FE change

Dynamic vehicle models were created using the Modelica modeling language [101]. These dynamic models utilize a combination of physical equations and lookup tables to define each subsystem of the automobile. A differential algebraic equation (DAE) solver is used to simulate the model using continuous time steps. The modeled subsystems include: Internal Combustion Engine (ICE), Motor/Generator (MG1 & MG2), Energy Storage System (ESS), Transmission (Tx), Final drive differential (Fd), Clutch, supervisory controller, driver, subsystem controllers, electric distribution block, and the operating environment. The automobile models have been designed and validated for both energy-use and vehicle dynamics [6]. Each of the modeled physical components has been developed with scaling parameters such that a range of different subsystem specifications can be represented (ex: different ESS capacity and nameplate power). Automobile characteristics from EPA testing documentation (as listed in Section 6.4.3) are used in calculating model parameters to represent each carline in the fleet.

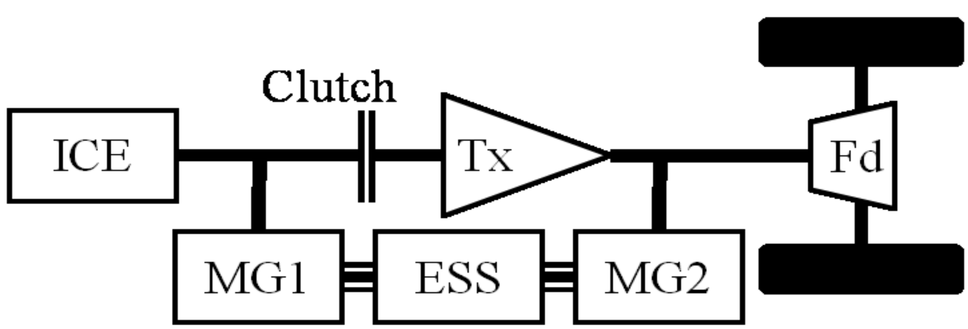

Figure 57 Modeled vehicle architecture.

To approximate all of the feasible architectures from the selected automobile production model years, a general Series-Parallel architecture was created. The modeled architecture is shown in Figure 57. By modifying the scaling components of the model this Series-Parallel architecture has the flexibility to exhibit characteristics of:

- A Conventional Vehicle (CV): by sizing MG2 as zero power, sizing the ESS as a 12V battery, and sizing MG1 as a starter motor.
- Pre-Transmission Parallel Hybrid: by sizing MG2 as zero power.
- Post-Transmission Parallel Hybrid: by sizing MG1 as zero power.
- Series Hybrid: by locking the clutch in the open position.
- Electric Vehicle: by sizing the ICE and MG1 as zero power

Using this method, hybrid automobiles can be represented as ranging from 'stop-start' to mild hybrid and full hybrid. These technologies correspond to a majority of existing and proposed topologies for the near-term US passenger vehicle fleet [15]. The control strategy for the modeled vehicle biases electrical propulsion (MG2) whenever available. A thermostat-type ICE control is used to maintain ESS state of charge within a specified range if in a charge sustaining condition as for HEV.

6.4.3.6.1 Automobile Parameter Definition

As mentioned previously, automotive vehicle design parameters such as total power and gear ratios have been obtained from the EPA dataset, and is reported for each carline. Unfortunately, EPA reporting is unspecific for electrified automobiles and does not include information on each carline's degree of hybridization. To translate the generalized EPA parameters into architecture-specific parameters the design rules in Table 17 were applied for vehicle models:

Table 17 Vehicle modeling rules used in this study

	MG1 Power (kW)	ESS Energy (kWh)
CV	0	0
HEV	Vehicle Power	0.018* Vehicle Power/350
EV	Vehicle Power	0.3* Vehicle Power/350

The above approach to modeling of HEVs and EVs allows the vehicle to have full performance in electric drive mode. In the case of HEVs the ESS is scaled using a factor similar to that of a Toyota Prius HEV. The EV's ESS is scaled to a factor similar to a Nissan Leaf. In all cases the ICE is set to have equivalent power as the rated vehicle power. This method results in more power potentially available at the wheels than the rated power (MG1 + ICE = 2 x Vehicle Power). This inconsistency is overcome by initializing all HEV's at their lower SOC set point and EV's at their upper SOC set point for each simulation. The different SOC set point initializations ensure that all energy for HEV's must come from fuel. In contrast, the energy for EV's will come from the ESS.

6.4.3.6.2 Baseline Automobile Performance Convergence

To reduce the inaccuracies associated with applying a unified vehicle platform to the wide range of vehicle architectures and configuration, additional system efficiency metrics were added to each vehicle's model. Two metrics were implemented; 1) total mechanical system efficiency, and 2) total electrical system efficiency. To obtain these values for each carline iterative simulations were performed until convergence was achieved between the reported fuel economy and the simulated fuel economy. Convergence was achieved based on Equation 19 for each vehicle.

Equation 19

$$\begin{bmatrix} |FE_{City,Actual} - FE_{City,Sim}| \le 5\,mpg \\ |FE_{Hwy,Actual} - FE_{Hwy,Sim}| \le 5\,mpg \\ |FE_{CH,Actual} - FE_{CH,Sim}| \le 1\,mpg \end{bmatrix} or\ [Iteration \ge 20]$$

A comparison of reported and simulated combined City/Highway fuel economy, based on the simplified EPA (55% City and 45% Highway) weighting, for each of the carlines is shown in Figure 58. Both the 2002 and 2010 simulated fleets independently achieved an R^2 above 0.98.

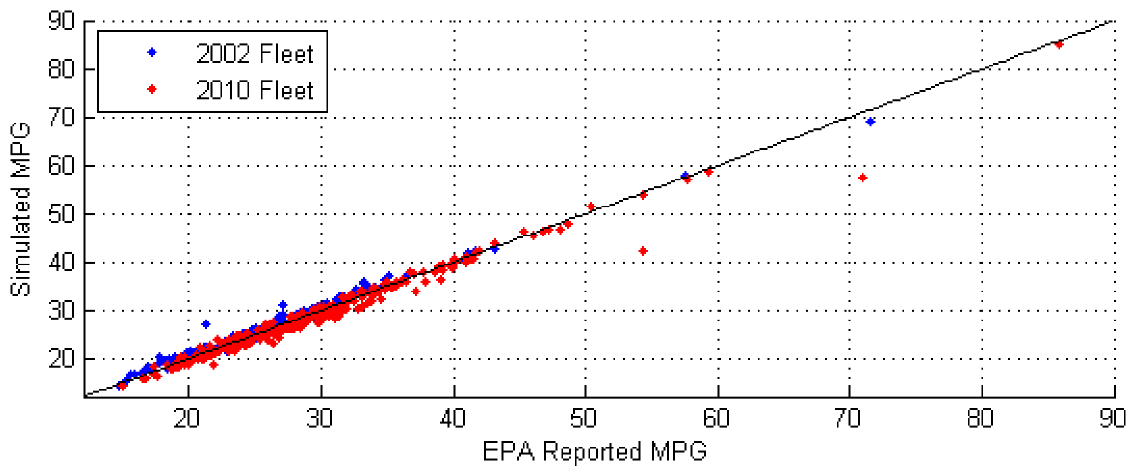

Figure 58 Regression of reported and simulated composite fuel economy[10].

It can be observed in Figure 58 that a few of the simulated automobiles did not meet the FE convergence criteria set by Equation 5 and instead encountered the iteration limit. To reduce inconsistency potential caused by these underperforming automobile simulations, all FE evaluations for this study will be based on incremental changes to the simulated FE and not the base or reported values.

10 The 2010 Nissan Leaf, at 142mpg, is not shown in the regression figure.

6.4.4 Results of Automotive Fleet Clustering

The following section will present the results of applying both the EPA classification method and the proposed clustering method to the simulated 2002 and 2010 MY fleets. Comparisons will be made to support the increased representativeness achievable by applying the proposed clustering method over previous EPA classifications. Results will be presented concerning the overall baseline performance of the grouped simulated fleets and the ability of each method to capture fleet response to technology improvements.

6.4.4.1 Baseline Grouping Results

It is found that each cluster linkage method generates different dendrograms. Based on the results we decided to perform the analysis using Ward's linkage method choosing 10 clusters. Table 18 shows the groupings that are used for this study. Note that the 2010 clustered vehicles have been grouped to the same 10 base clusters created for the 2002 vehicle fleet. In this was the cluster groups will provide some level of continuity across years, similar to EPA classes. Alternatively, vehicles can be re-clustered for each year's fleet to get a more accurate grouping, but with less traceability and lower predictive power for future vehicles.

Table 18 Vehicle groupings, group size, and exemplars.

	Clusters	**Clusters**	**EPA Class**	**EPA Class**
MY of Exemplar Vehicles	2002	2010	2002	2010
MY Used to Create Group	2002	2002	2002	2010
Number of Groupings	10	10	13	15

The cluster groupings successfully grouped vehicles based on multiple engineering characteristics. In contrast to EPA classifications, the clustering method allowed vehicles of similar characteristics to exist in the same group even when they would otherwise be separated by EPA classification. For example, the Ward's cluster method allows some large sedan cars, small SUVs and small trucks to be considered part of the same cluster group. Sports cars and high performance vehicles reside primarily in another cluster group (regardless of size or configuration), while HEVs, EVs, and high fuel economy vehicles belong to a third cluster group.

6.4.4.2 Prediction Results

To approximate potential improvements in vehicle technology contributing to fuel economy, three fuel economy improving treatments were selected for analysis: 1) reduced test weight, 2) reduced drag, and 3) increased hybridization. These improvements were selected to test characteristics that were both included in the clustering inputs (weight and dynamometer coefficients), and were not included (hybridization). The reduced test weight and reduced drag factors are applied by reducing the EPA-reported values by 10% for each vehicle when they are applied to the vehicle energy-use simulation. For the increased hybridization incremental technology each non-hybrid vehicle is modeled using the same design rules applied to hybrids from Table 17.

To demonstrate the advantage of using clustered vehicle groupings, Figure 59 shows box plots of the scaled fuel economy improvement observed through each of the incremental technologies as applied to each vehicle for both 2002 and 2010. The evaluation metric used in Figure 59 is calculated using Equation 20.

Equation 20

$$Scaled\ Distance\ (x, g, t) = (\Delta gpmi_{x,t} - \mu_{g,t})/P_{75(g,t)}$$

Where x is the index of each of the 304 vehicles in the 2010 fleet, g is the group number (for either clusters or classes), and t is the technology applied to the vehicle. The change in fuel consumption for each vehicle is represented by *Δgpmi* (delta grams per mile). The mean change in fuel consumption for each group within a technology application is represented by μ and is used to center the groups. P_{75} represents the 75th percentile of each technology application and is used to scale each value within a similar range.

For each treatment in Figure 59, the distribution of the scaled distance metric is presented for every vehicle in the fleet. The zero value identifies the mean fuel economy improvement among each of the groups, and within each treatment. Figure 59 shows that for both years and all technology increments the clustered groups are more centered and have less data spread than the comparative EPA classified vehicles. This achieves the objective of demonstrating increased similarity in FE performance within groups.

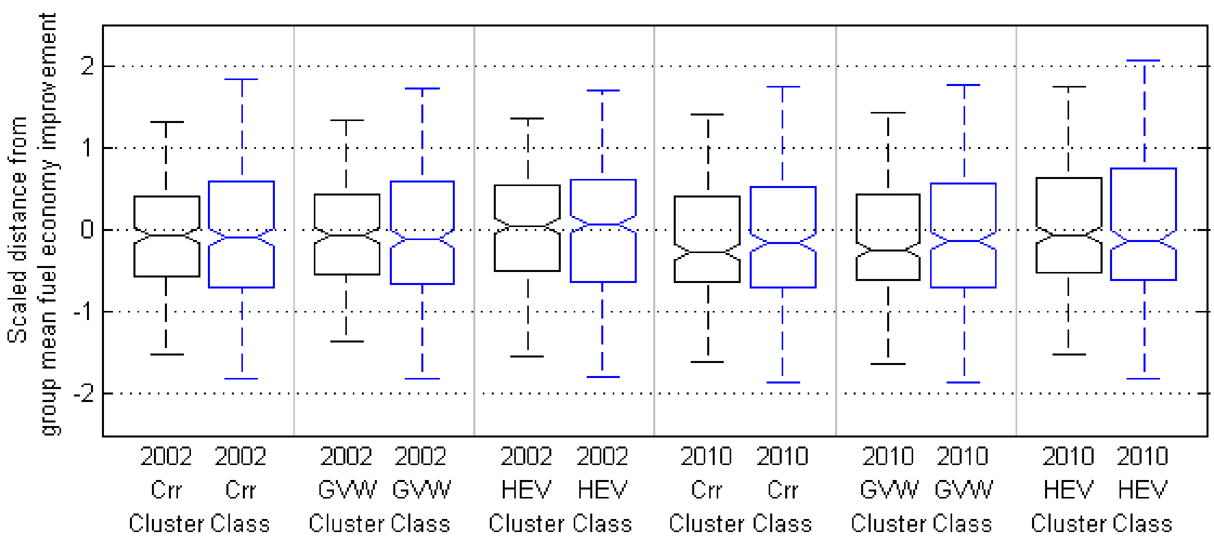

Figure 59 Normalized box and whisker plot of fuel economy gains from incremental technology changes by method and year.

As Figure 59 shows, for all technology treatments and years except one, the clustered vehicles perform more similarly to the mean of their group than do the vehicles grouped by EPA classes. This is particularly important when we consider that there is a better opportunity for the EPA classified vehicles to perform well since they have been divided into more groups (13 groups for 2002 and 15 groups for 2010) than the clustered vehicle groups (10 groups). To strengthen this claim, Table 19 presents a comparison for the mean of all groups' standard error for each of the methods. In each case, the clustered vehicle groups have a lower mean standard error than their EPA classified counterpart. The lower mean standard error implies that the clustered vehicles perform more closely to their group mean than EPA classified vehicles.

Table 19 Comparison of standard errors for grouped fuel economy changes.

Mean Standard Error (fuel reduction)	**Reduced Drag** (90% Crr)		**Reduced Mass** (90% GVWR)		**Hybridization** (+MG, +ESS)	
Year	**2002**	**2010**	**2002**	**2002**	**2010**	**2002**
Clustered	1.70%	1.64%	1.72%	1.55%	4.32%	7.49%
EPA Classes	2.32%	1.80%	2.37%	1.71%	7.17%	9.57%

The technology increment prediction results for both the 2002 and 2010 vehicle fleets show that using the clustering method provides a better way of grouping vehicles in relation to their energy-use performance. The results shown here are strengthen by the fact that fewer groups are used when clustering than for comparative EPA classifications.

6.4.5 Discussion of Automotive Fleet Clustering

The baseline results have shown that the proposed cluster grouping method is able to provide higher performance for fleet representation and prediction. The following methods will expand upon the benefits of incorporating automotive clustering into fleet-level automobile studies. Comparisons will be made with previous studies, all of which identify automotive clustering as a superior method for providing robust fleet representativeness.

6.4.5.1 Comparing the Effect of Technology/Design Improvement between Study-Selected and Cluster Representative Fleets

In the coming years, automakers will choose among a suite of technologies to devise a portfolio of automobiles capable of meeting the proposed CAFE regulations with minimal costs. In many cases, researchers and policy makers will rely on a subset of representative vehicles to evaluate the potential gains and limitations of technological advances.

To approximate these studies, representative vehicles have been selected from the cluster groups and a 2002 EPRI study [106]. The vehicles used in the study are listed below. Representative clustered vehicles were selected from the top three fleet sales groups, and median sales vehicles within each group. The representative vehicles from the 2002 fleet used for comparison are:

- EPRI Study: Saturn SL1, Ford Explorer, and Chevrolet Suburban.
- Clustered: Volkswagen Beetle, BMW 325, and Mercury Mountaineer

To many observers, the representative vehicles identified using the cluster groups may not be as intuitive of selections as the EPRI-selected vehicles. The validity of selecting the clustered vehicles can be shown through comparing the representative automobile integrated fuel reduction for each of the simulated technologies, as shown in Table 20. The simulated baseline fuel reduction for the entire vehicle fleet (all carline-specific fuel reductions integrated over all vehicles sold) is also provided in Table 20. It can be seen that for each incremental technology the clustered vehicles' more closely represent the entire 2002 US vehicle fleet than the EPRI-selected vehicles.

Table 20 Comparison of 2002 vehicle groups using three vehicles

Fleet gallons per mile reduction	**Reduced Drag** (90% Crr)	**Reduced Mass** (90% GVWR)	**Hybridization** (+MG, +ESS)
Simulated Baseline Fleet	3,491 gpmi	3,485 gpmi	61,496 gpmi
Clustered 3 Exemplars	3,549 gpmi	4,079 gpmi	36,354 gpmi
EPRI-Selected 3 Exemplars	3,338 gpmi	4,296 gpmi	155,780 gpmi

The fleet gallons per mile reduction metric used in Table 20 is calculated using Equation 21. Where n is the number of vehicles in the fleet and *MY Sales* is the sales for each vehicle model during that year.

Equation 21

$$gpmi\ Reduction = \sum_{x=1}^{n} \Delta gpmi_x \times MY\ Sales_x$$

On average, the EPRI-selected vehicles miscalculate the US fleet by 60% while clustered vehicles miscalculate by less than 20%. This difference is significant when considering that many fuel economy studies allow 15% error as an acceptable margin when simulating fuel economy [4]. The ability of representative clustered vehicles to more closely approximate the entire vehicle fleet provides great utility to researchers by providing a reduced number of vehicles that should be evaluated. As presented in previous sections of this study, ten cluster groups were identified as optimal for representing the vehicle fleets. The next section will show how using the increased number of representative vehicles can provide an even better approximation of fleet performance.

6.4.5.2 Comparing the Effect of Technology/Design Improvement between the most Representative Vehicles and Fleet

When performing evaluation of potential technology and design improvements for the US fleet it would be ideal to consider all vehicles sold within the fleet. For most investigations, simulating the entire fleet is considered infeasible due to computational cost. To demonstrate fleet-level representativeness of the clustered vehicles ideal ten cluster groups, each with a representative vehicle will be used in comparison with both the entire fleet and representative EPA classified vehicles. To provide a more equivalent basis, the top ten sales EPA classes are selected from the available 13 from 2002 and 15 from 2010. Simulated fleet-integrated fuel reduction (using Equation 7) for each of these methods is shown in Table 21.

Table 21 Comparison of 2002 and 2010 using 10 vehicles.

Fleet gallons per mile reduction	**Reduced Drag** (90% Crr)		**Reduced Mass** (90% GVWR)		**Hybridization** (+MG, +ESS)	
Year	**2002**	**2010**	**2002**	**2010**	**2002**	**2010**
Simulated Baseline Fleet	3,491	2,103	3,485	2,402	61,496	61,432
Clustered 10 Exemplars	3,531	2,092	3,565	1,963	58,717	53,136
EPA Classes 10 Exemplars	3,135	2,527	4,468	1,697	83,051	97,037
EPRI Selected 3 Exemplars	3,338	2,275	4,296	2,891	155,780	8,047

For each of the six cases investigated, the representative clustered automobiles perform more similarly to the baseline fleet than either the ten EPA classed vehicles or the three EPRI-selected automobiles. Additionally, error from the 2002 baseline is reduced from 20% to less than 3% when ten representative automobiles are used instead of the previous 3 from Section 6.4.5.1. In comparison, the ten representative EPA classified automobiles show an average error of 25% for the 2002 fleet. This trend remains consistent for the 2010 simulated fleet wherein the clustered automobiles show an average error of 11%, EPA classified show 36%, and EPRI selected automobiles result in 38% average error. It should be noted that due to carline differences across years, the 2010 EPRI selected vehicles incorporates a replacement of the Saturn SL1 with the Chevrolet Cobalt as its General Motors platform successor in the “compact car” class.

6.4.5.3 Trend in Future Automotive Design

Grouping automobiles and identifying representative vehicles from the groups provides a limited amount of utility if the method cannot be extended into future scenarios. In the case of EPA classifications, additional classes have been added to the groupings over the years as outlier carlines enter the fleet and as the overall characteristics shift within their classes. As was mentioned previously, a time span of 2002 to 2010 is used in this study wherein the EPA classifications grew from 13 to 15.

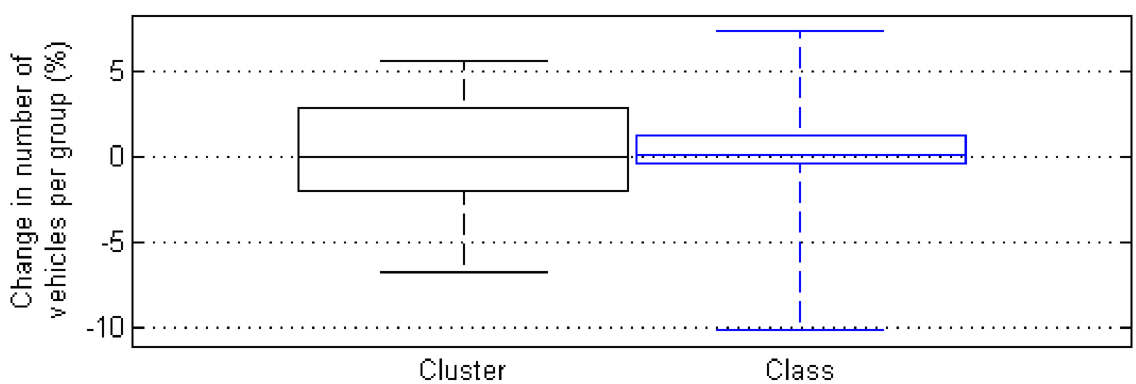

Figure 60 Comparison of group count changes from 2002 to 2010.

To demonstrate an ability to provide time-independent trends, the automobiles grouped using the Ward’s Linkage clustering method for this study for both 2002 and 2010 have been clustered into groups defined using only the 2002 fleet. To clarify, ten cluster groups were first defined using the 2002 fleet. Next, automobiles from the 2010 fleet were placed into the 2002 cluster groups. Using this method, the characteristics defining the ten cluster groups remains consistent over the 8-year period. The fuel economy representativeness of the ten clustered groups has already been demonstrated in previous sections. To add to this, Figure 60 shows the percent change in number of vehicles in each group from 2002 to 2010 for each method. The reduced percentile spread of the clustered groups over classified groups shows that even as new vehicles enter the fleet, the cluster groupings remain relatively consistent in size. In contrast, the EPA classified vehicles undergo cross-class shifting as new classes are defined and re-defined, resulting in more spread of change of group size. The ability of clustered vehicles to remain more consistent over a significant time frame demonstrates increased robustness of the new method over EPA classifications.

6.4.6 Conclusion

This research has proposed a new method of automotive classification and demonstrated the new method's potential benefits for both researchers and policy makers. The new approach relies on using the Ward's Linkage method to cluster automobiles based on their EPA-reported characteristics. Ten cluster groups were identified as most desirable for this application. This approach has been shown to 1) improve the state of the art for automotive fleet-level studies based on fuel economy by providing relevant classification, and 2) reduce the scope of studies by exploring more efficient approaches to representative automobile identification.

6.5 Task 2.5 Determine the pathway for researchers to effectively apply vehicle simulation and analysis tools

Although not exhaustive, many simulation tools and methods of analysis have been identified and explored in this research. Each tool for simulation and analysis applies to a wide range of automotive energy-use simulation studies. The tools for simulation and analysis that have been explored in this section are 1) optimization algorithms, 2) uncertainty quantification, 3) drive cycles as CONOP, and 4) fleet-level analysis. In the process of developing research tools, many studies will likely encounter the situation wherein they must determine the tradeoff between applying additional efforts to include advanced methods such as these, and thus achieve higher utility results, or reduce upfront effort and achieve lower utility results. This tradeoff selection process will be discussed in this section.

All of the tools explored in this research have the ability to reduce long-term effort when performing scientific automotive energy-use simulation studies. The structured tools proposed here typically require an incremental additional effort during the formulation of studies' methods, but can achieve much more defensible, extensible, and robust results when applied. Evaluating which tools are most applicable to each specific study can be a difficult task. Much of the guesswork can be eliminated from a study's development by performing a thorough study development design process in which the available parameters, desired metrics, and predicted results must be determined. The author, through extensive research and use of the simulation and analysis tools, has developed the following heuristics.

6.5.1 Optimization algorithms

Optimization should be applied more readily to high-level models when evaluation time is minimal. Detailed models may benefit more readily from design of experiments and design space sampling; at least until the design space has been sufficiently constrained to reduce the scope of an optimization's computational costs. Stochastic optimization algorithms can cope with the non-linearity and complex cost functions commonly associated with automotive simulation research. The simulated annealing optimization algorithm offers high rates of improvement in fewer iterations if a global optimal is not required. If global optimal values are necessary then DIRECT is suggested for use.

6.5.2 Uncertainty quantification

Uncertainty will always exist in automotive research. It is the responsibility of researchers to understand the tools that they are applying and select those which minimize uncertainty associated with their objective metrics. The two highest risks with insufficient understanding of a study's uncertainty are 1) incorrect conclusion, and 2) incorrectly applied efforts. Even by providing a general understanding of the sources of uncertainty, such as those provided in this research, researchers should be able to significantly reduce the potential errors in automotive energy-use studies. It is not always necessary to determine the precise value of uncertainty and error associated with each portion of a study, overall values may be sufficient when they can be traced directly to the objective metrics.

6.5.3 Drive Cycles as CONOP

Drive cycles are most important to automotive studies when the vehicle is being evaluated on a system level. Automotive subsystem research studies commonly have the ability to isolate the subsystem from many environmental interactions for an ideal representation. For automotive research that interacts directly with the energy-use for propulsion of a vehicle, drive cycles can be very influential. Producing stochastic or more advanced drive cycles is not always necessary, for example the case of constrained-use vehicles such as delivery trucks. Stochastic drive cycles as CONOP are most effecting for vehicles with high variability in operational patterns such as many average passenger vehicles.

6.5.4 Fleet-level analysis

Applying fleet-level analysis to automotive energy-use simulation can significantly reduce the computational costs required when solutions are required for a group or fleet of vehicles. In the case of an individual carline's study, fleet-level analysis will have a reduced benefit/effort. Fleet-level analysis is also important for all studies attempting a representation of futures; wherein technologies, fuel pathways, architectures, carlines, etc. are being evaluated for future scenarios. In any study that is dependent on consumer/developer-based options for multiple automobile types, clustering can reduce the scope of energy-use simulation that is required to achieve a defensibly representative solution set. There are a variety of characteristics that can be selected to perform the clustering analysis for fleet grouping. It is up to the researcher to apply knowledge of the interactions between automotive characteristics and attributes in determining which factors are necessary to define a classification of vehicle. This knowledge should specifically be applied to identify which characteristics differentiate vehicles according to the desired evaluation metric, fuel economy is one example evaluation metric.

6.6 Discussion of Research Question 2

What are the characteristics of analysis tools used in vehicle energy-use simulation?

With the increased capabilities of vehicle energy-use simulation tools and increased research interest in system engineering, advanced analysis tools are required to obtain pertinent results and provide opacity to developing conclusions. The analysis tools investigated in this research include: simulation optimization, quantification of uncertainty, CONOPS, and fleet-level characterization. Each of these tools have been studied and applied in detailed investigations to determine how they can be best applied to research to improve the utility of solutions in an efficient manner. The valuable analysis tools discussed in this section are intended to provide direction for researchers performing automotive energy-use simulation studies.

The completion of tasks associated with research question 2, in conjunction with research question 1, provide both a means for performing vehicle energy-use simulation and the tools and methods that should be applied to obtain the most efficient and useful conclusions. This will contribute to answering research question 3 and the associated tasks, which focus on the implementation of the simulation and analysis tools investigated for this dissertation.

7 Synthesis of State-of-the-Art Automotive Simulation Methods (RQ3)

7.1 Task 3.1 Provide a Qualitative Overview of Automotive Energy-Use Simulation Methods.

In the previous sections of this dissertation, vehicle energy-use simulation studies have been shown to incorporate a range of simulation tools, analysis tools, study types, purposes, and industries. To effectively implement all of the aspects of vehicle energy-use simulation investigated in this research, researchers must understand how they fit into the larger study development process. The methods that have been investigated in this Dissertation are: 1) modeling and simulation tools, 2) optimization algorithms, 3) uncertainty quantification, 4) drive cycles as CONOP, and 5) fleet-level analysis.

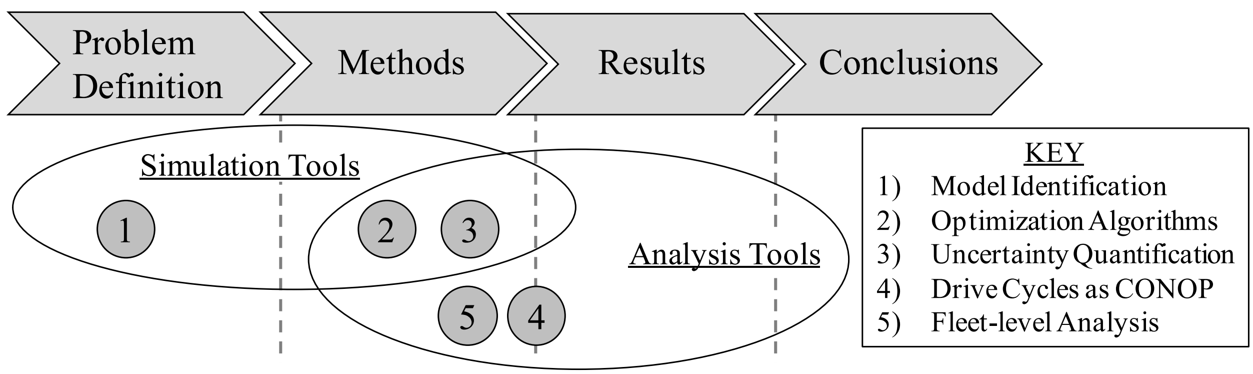

Figure 61 Relative occurrence of investigations within automotive energy-use simulation studies.

Within the framework of automotive energy-use simulation studies, a variety of possible tools and methods exist. Figure 61 provides a graphical representation of where the five key investigations from this dissertation fit into study processes. It can be noted that most of the investigated tools are biased towards early stages of the study process. Following system engineering principles, by applying more advanced methods early in complex processes, researchers can reduce the potential for re-evaluation or problem occurrence later in the process.

Typically, time spent early in a process is of a cheaper cost (time, effort, and monetary) than later in the process. As such, by applying these advanced methods early in the study development process, researchers can greatly improve upon automotive energy-use simulation studies as a whole.

In addition to improving the overall structure of an automotive energy-use simulation study, the methods and tools investigated in this dissertation also significantly reduce the computational cost required. Figure 62 provides a simple quantification of two possible study pathways, one that uses methods in this Dissertation (top), the other using previous methods (bottom). The values listed present the potential order of magnitude for simulation function calls when comparing studies with equivalent representativeness.

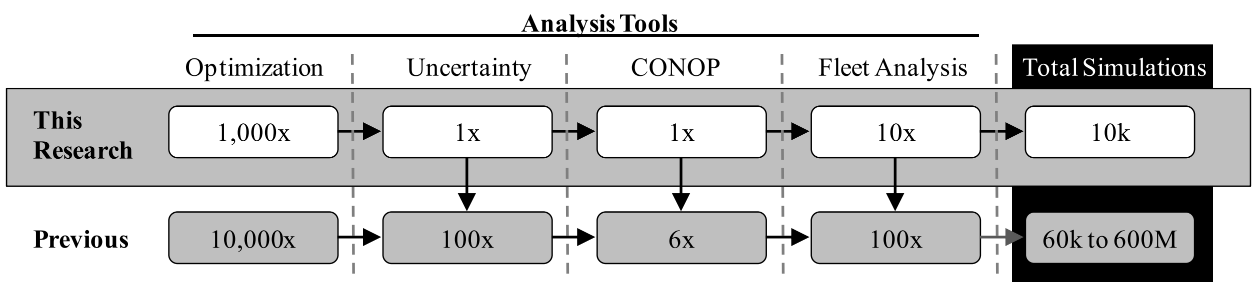

Figure 62 Comparison of required simulations for two equivalent studies, one using methods proposed in this dissertation, the other using previous methods.

As can be seen in Figure 62, the methods proposed in this dissertation have the potential to reduce the number of required simulation calls by over four orders of magnitude (10,000x) while retaining all information statistically. This is significant when considering many automotive energy use simulations range in computational cost between seconds to hours per call. The high value of the range in Figure 62 is based on the assumption that a researcher wishes to study automobiles on a fleet level using six drive cycles and optimization. Figure 62 also shows that although combining all methods investigated in this research can achieve the largest reduction in efforts, each individual method can assist in reducing computational cost of simulation studies while maintaining or improving validity of the results.

Having identified the advantages of using the methods proposed in this research, the following section will perform a comprehensive automotive energy-use simulation study that incorporates all methods. The results will then be compared with a previous study of the same objectives that did not use the proposed methods.

7.2 Task 3.2 Perform a vehicle energy-use simulation study using state of the art tools and methods.

Many well-cited and previously trusted automotive studies could have increased their utility by incorporating the methods proposed in this dissertation. To demonstrate the potential gains available through incorporating these methods, one such previous study will be recreated in part while applying the proposed methods. The study selected was originally performed by Kromer and Heywood at MIT [138] and proposed to evaluate potential vehicle technology pathways for the near future (next 30 years). This original study will henceforth be referred to as the "baseline study" for comparison. The baseline study attempted to quantify potential reduction in both petroleum consumption and greenhouse gas emissions (GHG) of in-use vehicles for the U.S. automotive fleet through vehicle modeling and simulation.

The following sections will first outline the methods used in the baseline study. The methods for this study will then be shown to build upon the baseline study methods while applying the new tools proposed through the research specific to this dissertation. Following the methods, a comparison will be provided between some of the primary conclusions from both the baseline study and this study. Discussion and conclusions will show that by applying the systematic tools proposed through this dissertation, more value can be gleamed from automotive research with minimal to reduced change in effort.

7.2.1 Baseline Study Methods

In an effort to condense the extensive methods presented in the baseline study, only those most relevant to the comparison presented in this dissertation will be overviewed. To represent potential future automotive technologies, five pathways were selected: conventional vehicles (CV), hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), battery electric vehicles (BEV), and fuel cell vehicles (FCV). Each of these technologies was modeled on a 2006 Toyota Camry platform. Each simulated vehicle architecture was required to meet the criteria shown in Table 22 in simulation.

Table 22 Criteria for simulated vehicles in baseline study

Design Criteria	Value
Acceleration (0-60mph)	< 9.3seconds
Gradeability	6% at 55mph
Drive Cycles	UDDS, HWFET, US06

Using a combination of heuristics and design iteration, these constraints were met while simultaneously attempting to achieve desirable energy-use performance. Vehicle mass considerations were taken into account, applying component-specific weight scaling based on respective parameters and also a glider mass compounding before simulation. The expected manufacturing costs, energy consumption, and emissions were calculated for each vehicle technology as applied to the Camry platform for the baseline study. For advanced technology vehicles (PHEV, etc.) a few (e.g. four) potential designs were considered to allow for variation in desirable Degree of Hybridization (DOH) and operating strategies.

7.2.2 Methods for this Study

Each of the vehicle architectures used in the baseline study will also be explored for this study. In addition, a fuel cell plug-in hybrid electric vehicle (FCPHEV) will also be added as a potential technology bridge for zero emission vehicles between battery electric vehicles and fuel cell vehicles. Figure 63 shows the six vehicle architectures considered for this study.

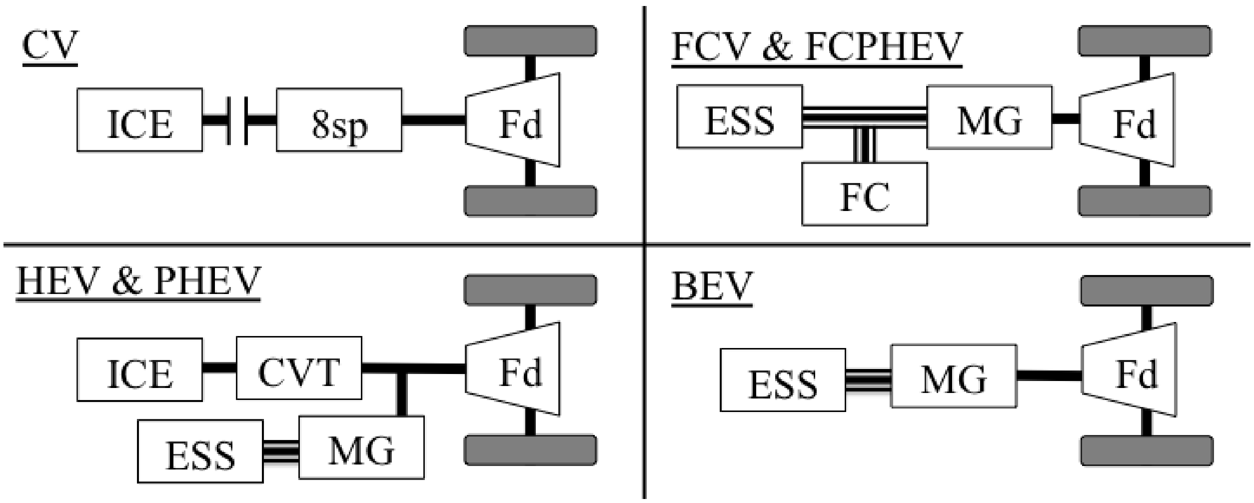

Figure 63 Vehicle architectures used in Research Question 3

In keeping with the format of the baseline study, only parallel HEV and PHEV configurations will be considered because they are proposed to offer the lowest cost per increased efficiency potential of the gasoline hybrid architectures.

7.2.2.1 Modeling and Simulation Platform

In keeping with other sections of this dissertation, custom vehicle models developed by the author using the Modelica modeling language are used for this study. The differential algebraic equation (DAE) solver DASSL was selected to compile the vehicle models for simulation. Together, Modelica and DASSL offer a modeling package that can quickly solve the type of physical equations, control strategies, and simulation conditions commonly associated with automotive systems.

For each modeled vehicle architecture, object oriented components were implemented with scalable parameters. The primary system components are listed in Table 23 with their abbreviations and descriptions.

Table 23 Research question 3 modeled automotive components

Component		Description
Internal Combustion Engine	ICE	Scalable model using max torque curve and fuel rate lookup table.
Energy Storage System	ESS	Scalable model using open circuit voltage, internal charge resistance and internal discharge resistance curves.
Motor/ Generator	MG	Scalable model using max torque curve and efficiency lookup table.
8 Speed Transmission	8sp	Automated manual transmission allowing for shifting with a clutch for reduced losses when compared to a torque converter transmission.
Continuously Variable Transmission	CVT	Continuous gear ratio changes within a specified allowable range, based on input speed.
Fuel Cell	FC	Polymer electrolyte membrane (PEM) hydrogen fuel cell. Scalable by number of cells, uses polarization curve and DC/DC converter.
Final Drive	Fd	Single gear differential for transmitting torque to wheels.
Controller and Driver	Cont	Provides requests for each of the subsystems to meet a driving schedule and perform energy management.
Auxiliary Load	Aux	Constant load applied to low voltage bus.

For architectures with plug-in hybrid capability (PHEV and FCPHEV), control allows for the vehicles to perform charge depletion with the ability to turn on fuel converting devices (FC and ICE) in the event that 1) more power is demanded by the motor (MG) than can be supplied by the energy storage system (ESS) or 2) the charge sustaining condition has been reached. State of charge is sustained between 35%-85% (50% depth of discharge) for hybrid vehicles and 15%-25% for plug-in hybrid vehicles. These values have been selected based on common OEM control practices for lithium-ion ESS. PHEV's begin their charge depleting simulated cycle with 100% SOC. The conventional vehicle architecture uses an 8 speed automated manual transmission (AMT) and is capable of ICE start-stop (performing fuel cut when the vehicle is stationary). Each of the modeled vehicles is subjected to a continuous 500W auxiliary load.

7.2.2.2 Optimization

An independent optimization is performed for each of the modeled vehicles. Based on the performance of stochastic optimization algorithms, as presented in Section 6.1, the simulated anneal algorithm was selected to perform the optimization. The minimized cost function applied was specific for each vehicle due to varying operational characteristics of the architectures. Note that final cost function values are not comparable across architectures, only the performance of the optimized designs will be evaluated. The general form of the cost function is shown in Equation 22.

Equation 22

$$Minimize: P_{Accel} + P_{Grade} + P_{Manuf\ Cost} + P_{SOC} + Fuel\ Consumption$$

Table 24 Criteria for simulated vehicles in this study

Design Criteria	Value
Acceleration (0-60mph)	< 9.3seconds
Gradeability	6% at 55mph
Manufacturing Cost	CV = baseline, Others= baseline+$5,000
State of Charge (CS)	Min(SOC) > lower SOC set point
Drive Cycles	UDDS, HWFET, US06, SC03, NEDC, NYCC

To identify only optimal vehicles able to meet the design constraints outlined in Table 24, severe penalty was applied on a continuous sliding scale for acceleration (P_{Accel}), gradeability (P_{Grade}), manufacturing cost ($P_{Manuf\ Cost}$), and state of charge (P_{SOC}). Each of the penalties was normalized to a unit less value that far exceeds the feasible range of fuel consumption such that their contributions to the cost function do not create tradeoffs. Fuel consumption is architecture specific, wherein plug-in vehicles are allocated utility factor weighting and the battery electric vehicle is optimized for maximum range. State of charge penalties (P_{SOC}) only apply to CS capable vehicles (HEV, PHEV, FCPHEV, and FCV) to ensure that they can operate in charge sustaining mode.

The design space for the optimization is constrained to keep component parameters within reasonable values (e.g. ICE power cannot be less than 0kW). Parameter limits are defined based on the component, and do not differ between architectures. The design variables for respective subsystems are presented in Table 25. This formulation results in a maximum of five design variables per architecture.

Table 25 Subsystem design variables for optimization.

Subsystem	Design Variables for Optimization
ICE	Maximum rated power.
FC	Number of cells (maximum rated power)
ESS	Maximum power and nameplate capacity.
MG	Maximum rated power.
8sp	Gear ratios.
CVT	Initial gear ratio.
Fd	Gear ratio.

7.2.2.3 Drive Cycles

In place of the previously used city (UDDS), highway (HWFET), and US06 cycles used in the baseline study, this study implements stochastic Markov cycles as discussed in Section 6.3. To expand upon the cycle requirements of the three original cycles, the SC03, NEDC, and NYCC are also included in the transitional probability matrix used to create Markov cycles. The expanded drive cycle considerations beyond the baseline study will aid in identifying vehicle more suitable for and representative of the U.S. automotive fleet. During each iteration of the vehicle optimizations, 100 unique Markov cycles are generated and the median cycle is selected for simulation. For vehicles with CD/CS strategies, two separate simulations are performed on the same selected Markov cycle; one beginning with a fully charged ESS, and a second that begins at the lower SOC managing set point. Vehicles are required to adhere to the drive cycle. Deviations from the drive cycle over 3mph are considered a failure to complete the cycle. This limitation is based on the EPA's 2mph allocation, which has been increased by 1mph due to using non-standard cycles.

Additional simulations are performed for each vehicle to determine 0mph to 60mph acceleration time and gradeability. Due to the inherent inconsistency of the Markov cycles, each vehicle is simulated on the standard UDDS and HWFET after achieving an optimal design such that they can be compared on an equivalent basis.

7.2.2.4 Fleet Representation

To expand upon the single vehicle selected by the baseline study (2006 Toyota Camry), this study incorporates the findings from Section 6.4 to provide a more representative set of vehicle carlines. Vehicle fleet clustering was applied to all carlines with available characteristics data as reported from the EPA. Ten clusters were found to be optimal. The top three sales clusters then each had representative vehicles identified from within the cluster. For this study, the three representative vehicles from the 2002 fleet are: the Volkswagen Beetle, BMW 325, and Mercury Mountaineer. The 2002 fleet was selected so as not to bias results based on automotive technology improvements that have occurred between 2006 and the 2010 fleet (the 2010 fleet being the alternative from the flustering study). Each of the three representative vehicles provides the baseline characteristics for the modeled and simulated architectures (3 carlines and 6 architectures =18 optimized vehicles).

7.2.2.5 Model Build-Up

To meet the requirements of the defined optimization cost function, within each function call calculations are performed for predicted incremental costs, added mass, and mass compounding effects. Mass calculations are applied to the models before simulation such that design variables of architectures are directly reflected in the simulated energy consumption instead of performing convergence calculations post-hoc.

The cost and mass formulations used do not represent the state of the art for automotive manufacturing at the time of the study. The rapid pace of automotive technology development makes it difficult to keep up with changing standards, and mass and cost data for scalable components is rarely available from manufacturers and usually only reaches researchers a short while after reaching the consumer market. The following cost and mass calculations from Table 26 are used for each simulated vehicle. The values have been obtained from a variety of sources including the baseline study [138].

Table 26 Subsystem design variables for optimization.

Subsystem	**Cost**	**Mass**
ICE	\$635 + 12 \$/kW	0.604 kg/kW
FC & H_2	75 \$/kW + 8 \$/kWh	0.4 kg/kW + 0.476 kg/kWh
ESS	\$1,230 + 175 \$/kWh	max(0.444 kg/kW, 0.120 kg/kWh)
MG	\$355 + 20.78 \$/kW	0.5 kg/kW
Tx	\$50	90 kg
Glider	2,000 \$/seat	300 kg/seat
Compound	N/A	72.5%

Representative vehicle cost and mass were calculated using the above formula in Table 26 using the characteristics of the three representative vehicle carlines. These representative vehicle costs and mass were also used as a preliminary check that calculated values are within reasonable ranges of reported values. Hydrogen fueled vehicles were assumed to begin with a capacity of 5kg onboard storage. Although the energy use simulations and desired range calculations may affect this value, the contribution of this deviation to the overall vehicle cost and mass is minimal (less than ± 0.2% Cost, ± 0.1% Mass). Based on previous study these values are orders of magnitude below the uncertainty levels for the simulated objective values.

7.2.3 Simulation Results

As was previously discussed, vehicles were optimized to have equivalent manufacturing cost and acceleration performance. Simulation optimizations were performed on the six architectures, as applied to each of the three representative vehicles. The results of the optimizations are presented in the following figures. Figure 64 shows the optimized manufacturing cost values. As a reminder from Table 24, all architectures except for the CV are allocated a $5,000 increment for advanced technology. It can be seen in Figure 64 that most of the vehicles are able to identify desirable designs very near the optimal cost. It should also be noted that all optimized vehicles successfully met the gradeability and 0-60mph acceleration requirements. The ability of all optimized vehicles to conform to the constraints provides an equivalent basis for comparison.

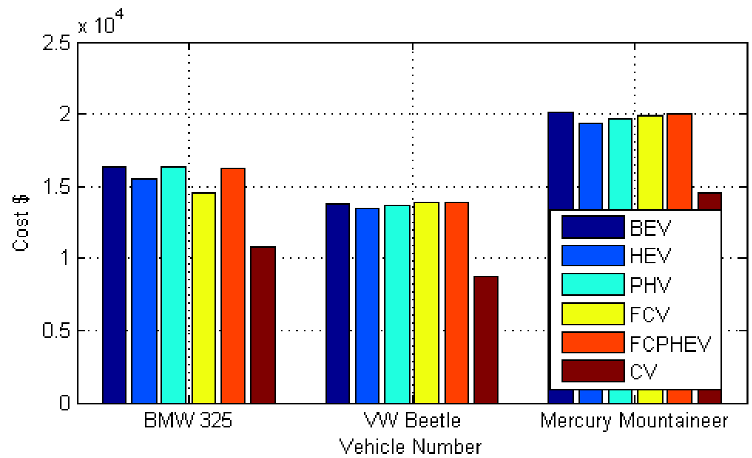

Figure 64 Optimized manufacturing cost.

Figure 65 presents the optimized values for battery (ESS) capacity for each of the 18 vehicles. Note that CVs have no onboard high voltage ESS and thus present zero values for each representative vehicle. A few trends can be observed in Figure 65 such as increasing FCV ESS capacity with increasing vehicle size. Some of the optimized architectures (PHV and FCPHEV) retain similar ESS capacities across the three representative vehicle platforms.

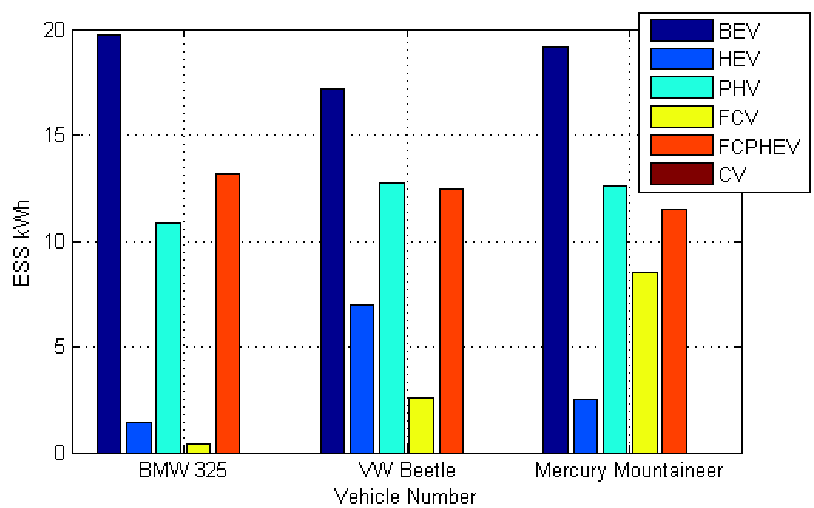

Figure 65 Optimized battery capacity for the 18 vehicles.

Figure 66 presents the simulated EV range for each of the vehicle architectures with a designed charge depleting capability. By comparing Figure 65 and Figure 66, it can be seen that even though some HEV and FCV have relatively large ESS capacities, they are not allocated plug-in capabilities and thus do not benefit directly from EV range. Figure 66 also shows that BEV consistently are optimized for the largest EV range within their platform, and optimal EV range decreases with increasing vehicle size, as would be expected.

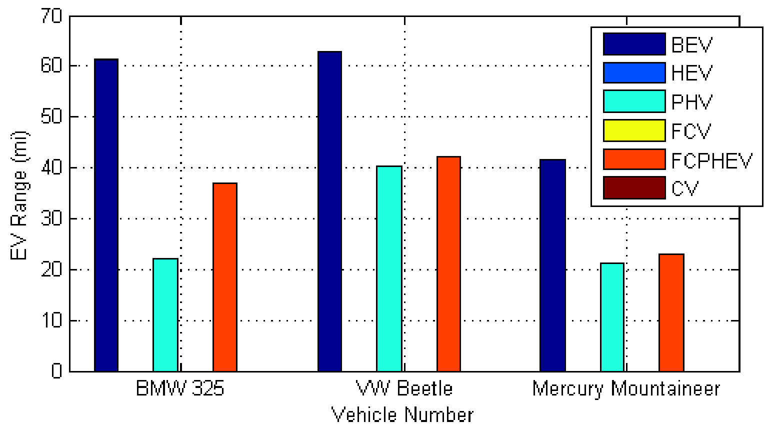

Figure 66 EV range for optimized vehicles.

For each of the architectures besides the BEV, a fuel converter is present to extend the vehicle's range. All optimized vehicle designs are required to be capable of charge sustaining over a single simulated cycle. The optimized power for each of the vehicles' fuel converters are presented in Figure 67. For gasoline powered vehicles (HEV, PHV, and CV) the fuel converter is an ICE, for hydrogen vehicles (FCV and FCPHEV) the fuel converter is the fuel cell. As would be expected, Figure 67 shows that as the vehicle size increases, so does the fuel converter power specification. It can also be observed that for the largest vehicle (Mercury Mountaineer) the ICE hybrids are able to significantly downsize. The PHV is capable of maintaining a relatively consistent ICE size across the three platforms.

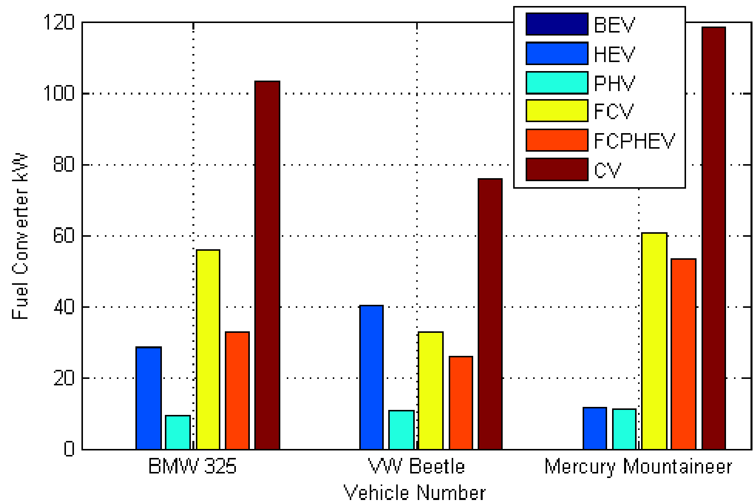

Figure 67 Optimized fuel converter power for the 18 vehicles

7.2.4 Discussion

To provide similar evaluation metrics to the baseline study, calculations are performed on the optimized vehicles to determine greenhouse gas emission (GHG) rates and petroleum energy use (PEU) rates. The conversion factors that have been applied to each of the vehicles' energy use simulation results are provided in Table 27. Values for Table 27 have been extracted from Argonne National Laboratory's Greenhouse Gasses, Regulated Emissions, and Energy Use in Transportation (GREET) model.

Table 27 Wheel-to-well greenhouse gas emissions and petroleum energy use allocations per fuel.

	GHG Emission Rate	Petroleum Use
Gasoline	10,851 g/gallon	1 gal/gallon
Hydrogen	11.8 g/gH_2	9.88e-6 gal/g H_2
Electricity	398 g/kWh	1e-3 gal/kWh

To calculate the rate of GHG and PEU for plug-in capable vehicles, the SAE utility factor (UF) weighting is applied based on EV range capabilities as presented in Figure 66. Plug-in vehicles are allocated emissions UF weighted GHG and PEU for both the CD and CS portions of their driving. The GHG rate for each of the optimized vehicles is shown in Figure 68. Similar to findings from the baseline study, smaller vehicles are more likely to present reduced GHG potential using gasoline hybrid and BEV configurations. Additionally, larger vehicle platforms were not represented in the baseline study and thus did not identify the potential for FCV in large vehicle platforms as shown in Figure 68. This trend is likely a resultant of the increasing ESS capacity for FCV with platform size. Detailed analysis shows that the large FCV (Mercury Mountaineer) is operating in a semi-blended control strategy but is still able to keep the SOC within the specified window. Charge balancing calculations may possibly reduce the advantage of the large FCV presented here.

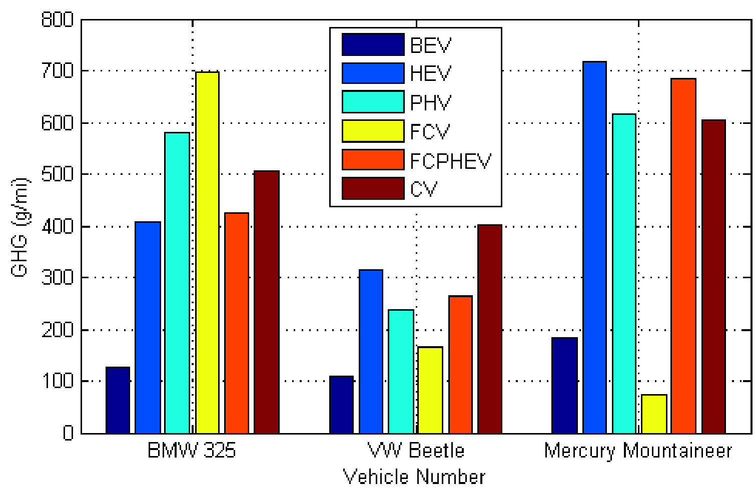

Figure 68 Optimized vehicle greenhouse gas emissions.

Using a strategy similar to that presented for GHG rates, PEU calculations also incorporate utility factor weighting of both the CS and CD portions of the vehicles' operation. PEU rates for each of the optimized vehicles is presented in Figure 69. It can be observed that tradeoffs exist between GHG reduction and PEU reduction for vehicles such as BEV, FCV, and FCPHEV as they exhibit high GHG rates, but low PEU rates. When considering both Figure 68 and Figure 69, it can be seen that BEV dominate a majority of the designs.

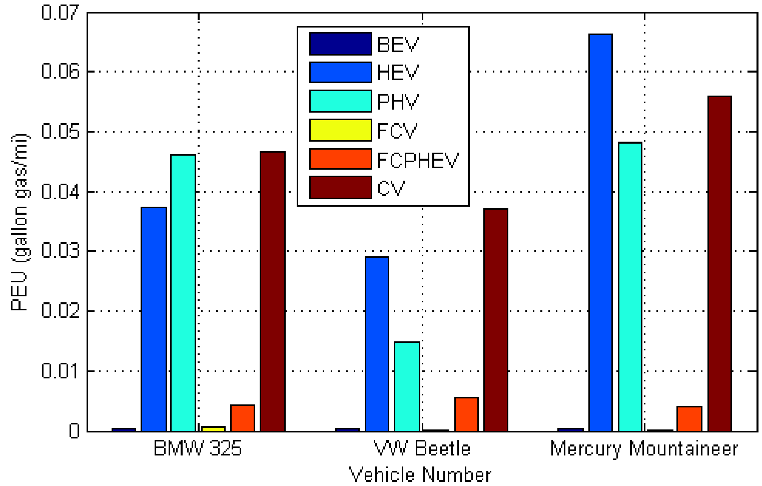

Figure 69 Optimized vehicle petroleum energy use.

The identification of the BEV as a potential pathway to reduce GHG and PEU across vehicle platforms must be coupled with the consideration for limited driving range, as presented in Figure 66. Additionally, the tradeoff between GHG and PEU rates must be quantified before an effective evaluation of all six architectures can be achieved. Excluding BEV from the evaluation temporarily, if the factors were to be evaluated on a normalized scale, FCV and FCPHEV can be identified as desirable vehicles for the VW Beetle platform. FCV exhibit high potential in the Mercury Mountaineer platform and FCPHEV exhibit high potential in the BMW 325 platform.

7.2.5 Conclusions

The baseline study shows similar trends to results found in this research for when considering a vehicle platform with similar characteristics (Toyota Camry and BMW 325). This result alone would lead a researcher to make similar conclusions as the baseline study. When the analysis is expanded to include the two additional platforms and the FCPHEV optimized in this study, contradictory conclusions can be drawn. For both the smaller vehicle (VW Beetle) and largest vehicle (Mercury Mariner) vehicles with plug-in capability (PHV and FCPHEV) as well as FCV present significant potential for both GHG and PEU reduction.

Infrastructure and range hurdles exist for implementation of both fully electrified vehicles and fuel cell vehicles. Previous research performed by the baseline study also suggested that manufacturing cost would be a potential hurdle for these technologies. By applying equivalent-cost constraints, and expanding the design space, this research has shown that plug-in and hydrogen fueled vehicles have desirable emissions and petroleum use characteristics. It is likely, that in a infrastructure-constrained market, plug-in vehicles (of both gasoline and hydrogen) will act as enablers for both BEV and FCV as the pathway towards more sustainable personal transportation.

7.3 Discussion of Research Question 3

What is the robust, defensible, and extensible structure of a vehicle energy-use simulation and how can it be applied?

Vehicle energy-use simulation requires researchers to acquire knowledge and experience with a wide range of tools. In addition to vehicle system principles, researchers must also understand the many model and simulation tools available as well as the methods for applying and performing analysis through a defensible scientific approach. The tools and methods that have been explored through research question 1 and research question 2 have been synthesized in research question 3 and then demonstrated in a comprehensive vehicle energy-use simulation study.

The structure of a robust, defensible, and extensible structure for vehicle energy-use simulation has been shown to exist at a system-level. Within the system-level approach, the required constructs for each simulation study can be effective identified. Applying a simulation tool capable of system-level representations is primary. To achieve high-value results, the methods of uncertainty quantification, optimization, CONOP, and fleet analysis must be included in the research methods.

Research question 3 has successfully implemented all of the research tools investigated throughout this dissertation and been practically applied to a comparable investigation with similar objectives. The baseline study for comparison is highly regarded in the field but has been shown here to be much more computationally expensive, and less defensible, than studies performed in this dissertation. The demonstrated research tools collaboratively make up the foundation for the advancement of future vehicle energy-use simulation studies.

8 Conclusion

Many challenges exist for research and design of future passenger vehicles. This dissertation has defined and completed a series of tasks to address the primary objective:

Provide an application-specific experimental method for conducting energy-use simulation of passenger vehicles.

The tools for modeling and simulation of vehicles for energy-use simulation studies have been identified, compared, and evaluated. Extensive research on modeling and simulation approaches has enabled assessment of these tools' strengths and weakness such that future researchers can select the tools appropriate for valuable studies. Interdisciplinary expertise has been developed for application in the automotive field including mechanical, electrical, thermal, control, environmental, marketing, and policy concepts. Based on a synthesis of requirements for state of the art energy-use simulation studies, a novel multi-domain modeling package was developed, validated, and demonstrated. The created vehicle modeling and simulation system was then applied to a suite of tasks that presently challenge advancement in the field of vehicle simulation studies. Optimization algorithms were identified with both deterministic and stochastic formulations and were evaluated on a complex multimodal simulated vehicle design space. Performing optimization on an unknown design space yielded questions towards identifying when optimal solutions had been located. To provide bounds to the compounding errors associated with the many assumptions and approximations that propagate through vehicle simulation, uncertainty quantification was performed for both the modeling and simulation tools. When optimization is applied to studies, the potential for increased quantity of system evaluations exists. For each increment, system evaluation cost can be compounded by the extent of conditions of operation and the number of represented vehicles. To reduce the burden of drive cycles used as conditions of operation for each vehicle energy-use simulation without sacrificing the content of a study, a new method of stochastic drive cycles was developed and demonstrated to have equivalent validity as the industry-standard computationally expensive approach. Additionally, statistical analysis was applied to automotive fleet-level analysis to perform clustering and identify representative exemplars. These representative exemplars have been shown to be more robust and less computationally expensive than previous industry-standard fleet approaches.

Combining the knowledge and methods developed through this dissertation, recommendations for future researchers were synthesized. A comprehensive vehicle energy-use simulation study was also performed to demonstrate the advantages of these methods when evaluated against studies of a similar scope. The results of demonstrating the methods proposed in this dissertation exhibited the ability to now perform studies with up to a magnitude of four reduction in computational cost while retaining and increasing the utility of the results.

The vehicle energy-use simulation studies performed in this dissertation represent novel cross-disciplinary application of scientific methods to vehicle research. Systems engineering approaches have been emphasized throughout this dissertation towards improving the efficiency, robustness, validity, and extensibility of vehicle research. This dissertation is specific to the automotive field, founded on scientific principles, and structured by experimental method. The tools, methods, and analysis will prove to significantly improve the state of the field and enable researchers to perform advanced simulation energy-use studies for passenger vehicles.

8.1 Contributions of this Dissertation

The primary contributions of this dissertation are:

- An extensive review of automotive simulation energy-use literature
- A qualitative identification and evaluation of the tools available for vehicle simulation
- A modeling and simulation package capable of representing multiple vehicle architectures. The package has specifically been designed and validated to be fast, modifiable, and extensible.
- A quantitative assessment of multiple stochastic and deterministic global optimization algorithms as they apply to vehicle energy-use simulation.
- An identification of the five sources of uncertainty in vehicle energy-use simulation and quantification for each source.
- A developed novel method for condensing drive cycles as CONOP.
- Inception for a paradigm shift of how vehicle fleets are characterized.
- Synthesis and demonstration of the tools and methods paramount to eliminating the challenges presently retarding the advancement of automotive research.

8.2 Future Work

This dissertation builds a foundation for future vehicle energy-use simulation studies. The tools, methods, and analysis presented in this research do not claim to be comprehensive for the field. Future research and studied that hopefully implement the methods presented here are likely to identify new challenges that were previously unidentified or of an insignificant hindrance to the research process. As automotive technology, the consumer market, policy, and the global environment continue to evolve, the methods and tools must adapt with them. A struggle between progressing computational processing capabilities and advanced approaches will continue to push the limit of the information obtainable from simulation. When computer processing is the limiting factor, methods such as those developed in this dissertation will prevail. At some point, potential exists that the methods will advance to a state where they become the limiting factor. Regardless of these limitations, the scope of vehicle studies must continue to grow and encompass increasing system-level objectives and attributes.

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