Hybrid Powertrain Design Using a Domain-Specific Modeling Environment

Wenzhong Gao[1], Sandeep Neema[2], Jeff Gray[3], Joseph Picone[1],
Sachin Porandla[1], Shravana Musunuri[1], J. Mathews[1]

Abstract—State of the art design tools in automotive engineering still lack the power, sophistication, and automation of design tools that are used in the electronics industry. Widely accepted automotive powertrain design tools such as PSAT and ADVISOR still rely on manual manipulation of the design parameters for optimization. This paper presents a new methodology that merges model-based design, knowledge-based engineering, and physics-based modeling to realize large-scale design optimization. The extensible domain-specific design environment is capable of rapidly assimilating new knowledge from experts and design database. Further, it can be used to automate the management of design knowledge in a customizable manner. Introducing a design process that can handle the complexity of millions of competing constraints in an automated way will allow automotive manufacturers to reduce design time considerably.

Index Terms—**Domain specific modeling, GME, Hybrid powertrain, Optimization, Physics-based modeling, Bond-graphs.**

I. Introduction

From prototype design to final product manufacturing, modern automotive systems are experiencing a phenomenal growth in the deployment of new hybrid powertrain configurations and embedded controllers, and other associated technologies for disparate applications. With continuing advances in computing power and performance, it is imperative for automotive software engineering to remain connected with the innovations of new technologies and the increasing needs for better design tools. Nowadays, automotive software engineering is seen as a driving force for the innovation of new capabilities, coupled with cheaper technical solutions [1, 2].

The complexity of new designs and dependence on embedded software is proving to be a cause of concern to automotive manufacturers. This results in an increasing difficulty in predicting interactions among various vehicle components and systems. Effective diagnosis also becomes problematic. As an example, the well-known worldwide recall in Spring 2002 of the BMW 745i was a direct result of the software failures associated with the "iDrive" control system, which controls over 700 onboard functions through embedded software. This 'Achilles heel' syndrome is also being experienced in contemporary design tools for automotive engineering. A face-off with modeling and simulation tools in the electronics industry has demonstrated that similar tools in the automotive domain still lack the power, sophistication and automation available to electronics designers [1]. Advances in electronic design tools have validated Moore's law (as applied to the complexity of integrated circuits) and have helped achieve amazing standards in computing power while simultaneously decreasing costs. For designers of automotive systems to duplicate and manage similar levels of complexity, design tools that automate the low-level details of the design process need to be developed [1].

In this paper, a new design methodology is presented that merges concepts of model-based design, physics-based modeling, knowledge-based engineering, and large-scale design optimization. The rest of the paper is organized as follows: Section 2 provides an overview of the design methodology. Section 3 elaborates upon domain-specific modeling and its application to the powertrain design. Section 4 applies physics-based modeling techniques to automotive engineering design. Section 5 and Section 6 delve into the specifics of powertrain design and optimization. Finally, preliminary results and conclusions are given in section 7 and Section 8, respectively.

II. Architecture Overview

A domain-specific design platform that incorporates physics-based modeling, human design knowledge, optimization functions, and design databases is shown in Figure 1. This platform can be applied to a wide range of automotive design problems and can be integrated with a wide variety of industry-standard tools. One of the key objectives in the automotive design is to parameterize the design expertise of experienced automotive engineers and embed this

[1] Wenzhong Gao, Jospeph Picone, Sachin Porandla, Shravana Musunuri, Jimmy Mathews are with the Center For Advanced Vehicular Systems, Mississippi State University, Starkville, MS 39759. (e-mail: {wgao,picone,skp46,musunuri,mathews}@cavs.msstate.edu)

[2] Sandeep Nema is with Institute of Software Integrated Systems, Vanderbilt University, Nashville, TN 37235. (e-mail: sandeep@isis.vanderbilt.edu).

[3] Jeff Gray is with the Department of Computer and Information Sciences, University of Alabama Birmingham, Birmingham, AL35294 (e-mail: gray@cis.uab.edu)

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knowledge within the loop of the optimization process. Powertrain design is a target testbed to develop and refine this methodology.

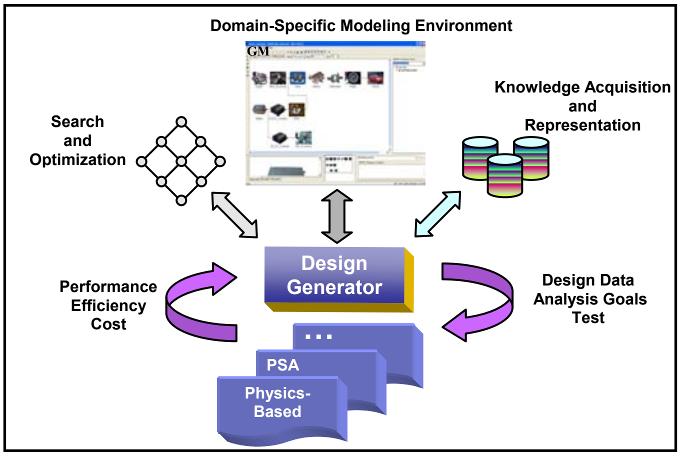

Fig. 1. Design Framework

The key ingredients of this approach are:

- methodologies for knowledge representation of design experience via domain-specific modeling languages (DSML) and automated capture of this information using machine learning techniques;
- physics-based modeling techniques that will enable high-fidelity simulation and design using standard modeling languages such as IEEE VHDL-AMS;
- knowledge-based optimization algorithms to maximize efficiency and fuel economy and minimize emissions, which are critical to the acceptance of these tools in the automotive design community.

A high-degree of design automation achievable in this methodology helps in reducing both the cost and design time. Due to the large volume of production in the automotive industry, even small savings per vehicle translate into tremendous revenue for the industry [3]. This methodology also advances the fundamental understanding of how expert designers accumulate experience and make design decisions. The extensible design environment discussed in the paper will be able to assimilate additional knowledge rapidly as new designs become available. Further, it can be used to automate the management of design knowledge and can serve as a training utility for new engineers.

The following sections briefly elaborate the key technology components that are employed in this application.

III. Domain Specific Modeling Environments

The automotive sector was one of the first to adopt model-based design technology on a broad scale. Model-based design provides a good basis for addressing system complexity and other problems, primarily because they are based on a separation of the problem-solving algorithm from the model and the compositionality of the model [1]. An example of the type of productivity that can be achieved from modeling, as applied to manufacturing in the automotive domain, is provided in [3].

The analysis and design techniques in traditional model-driven development (MDD) describe the architecture and the relationships that must exist in software. Additionally, MDD also provides the capability of modeling the external interfaces to the system's environment. However, models in such systems are loosely coupled to the actual development cycle, thereby affecting the functionality, performance, and reliability of the systems. *Model Integrated Computing* (MIC) [4, 5, 6] is a well-suited approach for the rapid design and implementation of systems where the software, the environment, and the integration constraints are all modeled. The resulting integrated, multiple-view models are used to configure and generate the necessary software components of the actual system and to capture the information relevant to the system under design [7, 8].

MIC tools provide the capability to model characteristics of any domain by providing customization of a modeling environment through metamodels, which describe the essential entities and connections among them. Metamodels are the specification for a domain-specific modeling environment (DSME). The DSME can then be used by domain experts to construct representations of systems in that domain. The models are typically graphical and domain-specific and are stored in a model database.

The Generic Modeling Environment (GME), a flagship tool of MIC, illustrated in Figure 2, provides a solution to the longstanding requirement in software engineering, particularly in the automotive sector, for the development of modeling environments that can be easily modified and extended. The GME is a meta-configurable tool for creating and evolving domain-specific, multi-view models of large-scale engineering systems [8]. It is configurable, thus having the ability to work in different domains and is particularly useful in the design of complex systems like hybrid powertrain.

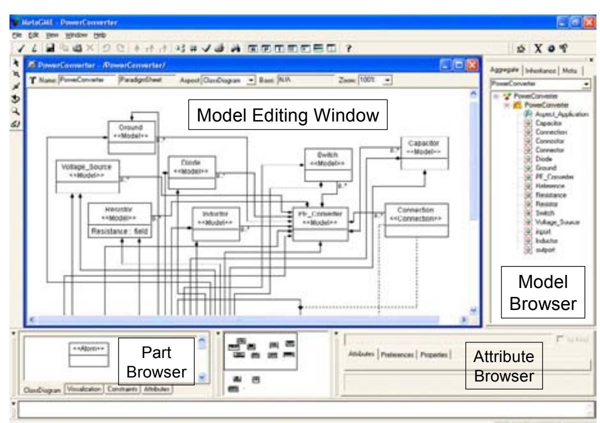

Fig.2. The Generic Modeling Environment

In addition to the model design, the embedded software also could be modeled in the GME. Figure 3 shows the modeling of the Electronic Throttle Controller (ETC) software in the GME. This gives a clear indication of the capability of the GME to model an application as well as to model the software used in that particular model.

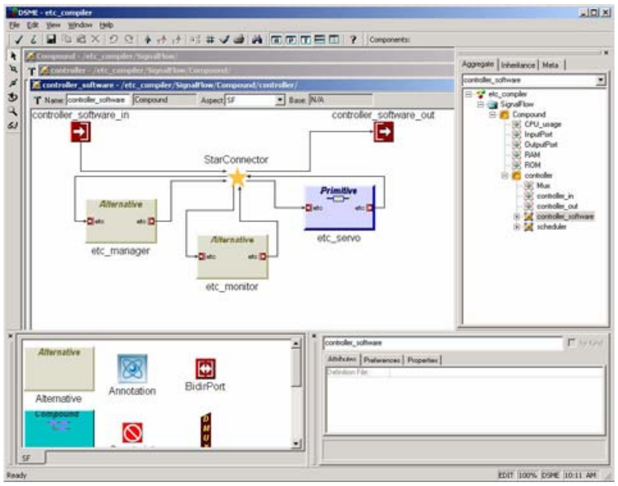

Fig.3. The Electronic Throttle Controller modeled in GME

Our initial work has adopted the GME as a key technology to support our vision of improved powertrain design. A domain-specific modeling language is being constructed to address the special features needed for powertrain design and integration with physics-based modeling techniques, machine-learning techniques, and other tool suites such as optimization tools and SABER.

Modern modeling tools, such as the GME, are characterized by a greater flexibility of reuse and flexibility to support the modeling of physical entities in software. In the powertrain design, GME allows the exploitation of a range of possibilities offered by the hybridization of powertrains, unlike a majority of simulation packages that are based on fixed powertrain layouts. In addition, the GME also provides the capability of setting constraints on the models, if required, which prevents any erroneous design. All these advanced functionalities form the crux of an attempt to develop a set of robust, multi-configurable tools for "Intelligent Powertrain Design".

It is also possible to co-simulate the design process of a system with other design software like MATLAB/SIMULINK, etc. The model interpreter for the model developed in GME can generate a Matlab script file, which then could be included in the MATLAB/SIMULINK environment. For example, the execution of this script file can generate Simulink–Stateflow models [9]. Any changes that are needed to be made in the design process could be made easily in GME.

All the above features could be used in an efficient way in the design and modeling of a complex system like hybrid powertrain. The following sections outline key characteristics of powertrain design that can be improved through a configurable modeling tool like the GME.

IV. Physics-Based Modeling

Existing powertrain design tools [10] are based on experiential models, such as look-up tables, which use idealized assumptions and limited experimental data. The accuracy of these tools may not be good enough for vehicles operating under extreme conditions. On the other hand, the designs may lead to components or systems beyond physical limitations. To make design optimization effective, models must be tied closely to the underlying physics through a link such as a lumped-coefficient differential equation or some digital equivalent computer model. Only then can it be assured that the subset of physically-realizable models will be searched and that real-world constraints will guide the design to a meaningful optimum. In physics-based modeling, the state variables of a component or subsystem are modeled according to the physical laws representing the underlying principles. The resulting model is a function of device parameters, physical constants, and variables. Such physics-based models can facilitate high fidelity simulations for dynamics at different time scales.

In our study, two physics-based modeling techniques – Resistive Companion (RC) [11] modeling and Bond Graph (BG) [12] modeling – are explored. The RC method originates from electrical engineering, while the BG originates from mechanical engineering. Both methods are suitable for multi-disciplinary modeling applications and together could be used for efficiently modeling and designing a complex system like hybrid powertrain.

The RC method has been used successfully in a number of industry-standard electronic design tools such as SPICE and SABER. Recently, it has also been applied in the Virtual Test Bed [11], which is being recognized as the leading software for prototyping of large-scale, multi-technical dynamic systems such as those found in electric ships. Using the Resistive Companion Form (RCF) modeling technique [11], we can obtain high-fidelity physics-based models of each component in modular format. These models can be seamlessly integrated to build a system simulation model suitable for design. Just as a physical device is connected to other devices to form a system, the device can be modeled as a block with a number of terminals through which it can be interconnected to other component models, as shown in Figure 4.

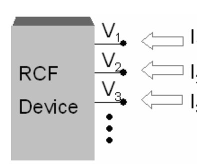

Fig.4. Physics-Based Resistive Companion Form Modeling Technique

On the other hand, in Bond Graph modeling, a physical system is represented by a collection of components that interact with each other through energy ports [12]. It is a powerful tool for modeling engineering systems, especially when different physical domains are involved. The physical structural information is conserved. BG uses analogous power and energy variables in all domains, but allows the special features of the separate fields to be represented. The only physical variables required to represent all energetic systems are *power variables* (effort (e) & flow (f)) and *energy variables* (momentum p(t) and displacement q(t)). There are several BG-based commercial software packages for modeling and simulation of dynamic systems (e.g., CAMP-G [13] and 20-Sim [14]). BG method has also been applied to the modeling of hybrid vehicle powertrain [15].

V. Powertrain Design

Hybrid powertrain design depends on the mission and performance requirements of a vehicle and its application. Design flexibility for hybrid powertrains requires evaluation of a large number of options and complex non-linearities that exist among various components. It is difficult for designers to reach an optimum tradeoff among various design criteria (e.g., size, efficiency, cost, weight, and volume) using a manual tool. Current powertrain design tools are not suitable for such optimal design and do not facilitate the reuse of expert knowledge. These factors, along with the large design space, necessitates the use of novel automated search techniques for achieving the near optimal design. To address these challenges in powertrain design, domain knowledge extracted from experienced designers along with the standard optimization techniques have to be integrated into an extensible computer-aided design platform.

This combination of large-scale design optimization and knowledge–based engineering will result in a unique powerful intelligent design software package for hybrid electric vehicle powertrains. The immediate benefits are the improvement of the design in terms of cost and performance and the reduction of the number of design iterations. The desired goal can be achieved by employing methodologies for knowledge representation of design experience using a DSME and automated capture of knowledge using machine-learning techniques.

The key areas in defining design methodologies are physical design, simulation/verification, synthesis, and testing. The main reason for the success of automated engineering design is that a higher-level of abstraction can be established so that all the device-level and process-level details can be shielded from the higher-level design. The electronic design automation (EDA) employed in the design of analog and digital circuit is an example for such a design methodology. The achievements of EDA can serve as a model for developing design tools for analog based complex engineering systems like automotive powertrains. However, unlike digital design, analog design is less systematic, more heuristic and knowledge-intensive in nature. This makes the powertrain design more challenging when compared to digital circuit design.

VI. Design Optimization

Optimization is an area receiving much attention in automotive design [16, 17]. The availability of many configurations, control strategies, and design variables necessitates the use of mathematical modeling and design optimization to find the best overall design. Thus, the optimization process becomes a problem of large-scale multi-objectives (e.g., maximum fuel economy, minimum emissions, minimum cost). There are two types of optimization methods that can be applied to automotive design: equation-based and simulation-based. The equation-based method is not practical due to the difficulty in obtaining analytical objective functions in terms of the design variables. On the other hand, with the improved computation power, advanced numerical algorithms can be looped with a simulation model to achieve simulation-based design optimization. Although classical numerical optimization techniques can be used, statistical methods (e.g., simulated annealing and genetic algorithms) seem more effective in avoiding local minima in the search-space.

Optimization techniques have been applied in the design of power converters, which are critical functional components of any hybrid powertrain. Various optimization tools have been developed for meeting certain requirements. For example, a design optimization tool that minimizes materials cost for a boost converter was developed based on a genetic algorithm [18]. This tool takes into account the design specification, physical limitations, and operational safety of the device. Another optimization tool based on CAD is used for the design of automotive DC/DC converters [19]. In this tool, the objective function is a weighted sum of component volume, weight, and cost. A Monte Carlo search method and expert system are used in the selection process of the components. A large number of iterations are necessary before an optimum design is reached. Unfortunately, this tool is very time-consuming and there is no guarantee that an optimum solution will be found.

Knowledge-based optimization has also been applied to the design of power converters. An expert system with a design knowledge base and automated computer-aided optimization was implemented in a CAD-Tool for the design of switched mode power supplies [20]. The expert system shell CLIPS was used. A knowledge base is used to select the best power supply topology according to the given design specification. A sub-knowledge base is used to select components based on the target volume, cost, and efficiency of the design. The knowledge base can also assist in the selection of the appropriate control scheme.

A classification of the optimization algorithms (gradient-based and non-gradient/derivative-free) used in a hybrid powertrain design environment is given in [21]. The gradient-based algorithms (e.g., Sequential Quadratic Programming [22]) works well for smooth, continuous functions, but often fail miserably for noisy, discontinuous functions because of the wrongly calculated gradients. Derivative-free algorithms (e.g., DIRECT [23] and COMPLEX [24]) can be used to avoid the gradient calculation problem. DIRECT (DIviding RECTangles) is an optimization algorithm designed to search aggressively for global minima of a real valued objective function over a bound-constrained domain without using derivative information [25]. Many toolboxes using the above mentioned routines are applied to analyze the hybrid electric vehicle optimization process in [10]. Algorithms based on the Expectation–Maximization algorithm are developed and shown in [26], which can significantly improve the convergence criteria compared to other algorithms. Based on our initial investigation, DIRECT and Expectation–Maximization algorithms are to be used in our powertrain design tool because these algorithms facilitate a knowledge-based search and simulation-based optimization.

VII. Preliminary Results

As a first step in the powertrain design, a metamodeling environment has been developed in GME for solving an electrical circuit involving basic elements like source, resistor, inductor, and capacitor in any circuit configuration. RCF technique was used in the dynamic modeling. The following figures show an application model developed in GME from this meta-model and the simulation results. The numerical results obtained are verified to be correct.

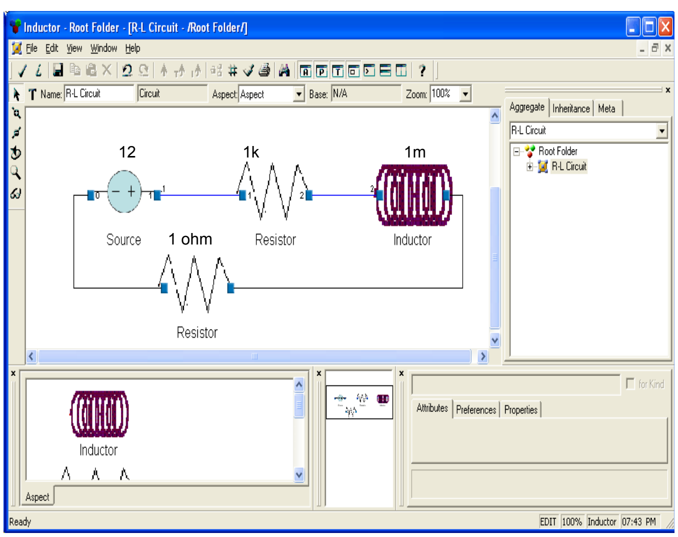

Fig.5. R-L Circuit in GME

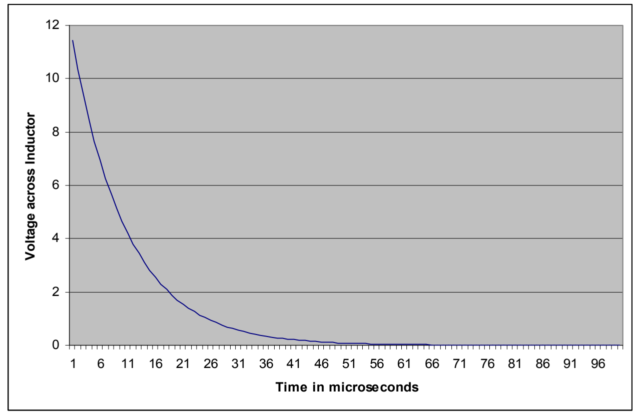

Fig.6. Voltage across Inductor

As an illustration of the modeling using Bond Graph technique, a Bond Graph metamodeling environment has also been created in GME and a DC motor is modeled as an application example, illustrated in Figure 7.

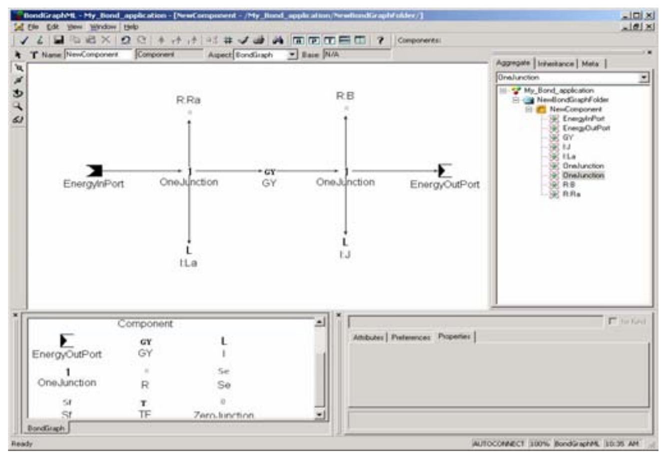

Fig.7. DC Motor Modeling using Bond Graph in GME

The RCF and bond graph techniques could be used efficiently in the design and modeling of other linear and non-linear multi-domain components and systems in GME. The hybrid powertrain, which is a complex combination of linear and non-linear elements and components, could be modeled in GME using the above techniques.

The hybrid powertrain configuration metamodeling environment created in GME allows for the incorporation of domain expert's knowledge and automatic check of the design constraints. The meta-model developed defines three aspects or domains (electrical, mechanical, power train) in which the vehicle design can be visualised with appropriate constraints set on each component. As an application example of this environment, models of series hybrid powertrain and parallel hybrid powertrain are developed, and are shown in powertrain aspect as illustrated in Figure 8 and Figure 9.

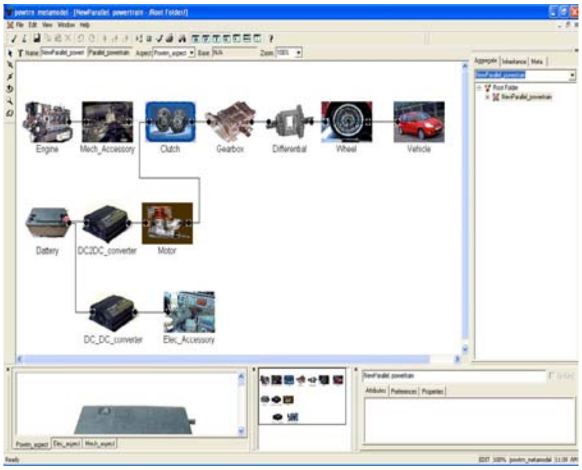

Fig.8. Parallel Hybrid Powertrain design in GME

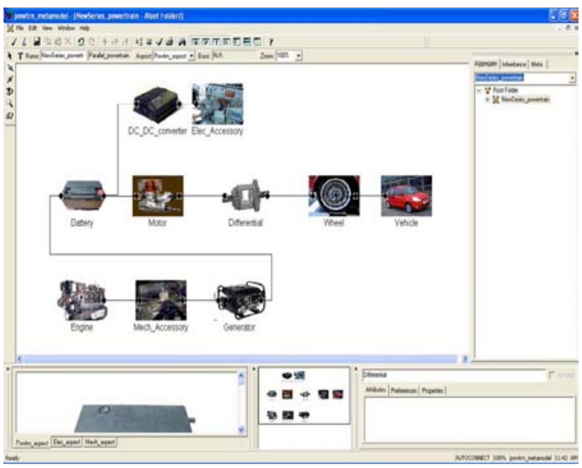

Fig.9. Series Hybrid Powertrain design in GME

It should be noted that this metamodeling environment allows for innovative powertrain configuration design, while setting constraints to maintain a physically realizable design. In our on-going effort, a new metamodeling environment that integrates the configuration of powertrain, bond-graph modeling together with optimization algorithm will be created. This domain-specific modeling environment will be used for hybrid powertrain design and analysis.

VIII. Conclusions

This paper addresses the issues facing contemporary automotive engineering design tools. It presents a new methodology for design automation by integrating model-based design, physics-based modeling, knowledge-based engineering, and large-scale design optimization in a domain-specific modeling environment. Such a design tool has the potential to bring significant cost savings, performance enhancement, and design time reduction for hybrid powertrains. Though the design of hybrid powertrain using the CDSME principles in GME is still in progress, the preliminary results and the proven capability of GME for advanced modeling and design strongly suggest the success of this design methodology.

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