Performance Enhancement of Hybrid Electric Vehicle using Internal Combustion Engine and Energy Management Subsystem

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ABSTRACT- This shift towards electric vehicles (EVs) is primarily driven by the commitment to reduce emissions and decrease reliance on fossil fuels, and at the heart of this transformation lies its drive system. EVs replace the conventional internal combustion engine (ICE) with battery-powered electric motors. However, several significant challenges hinder the widespread adoption of EVs, including battery limitations, energy density, charging speed, lack of charging infrastructure, high cost, and dependence on critical materials such as lithium and cobalt. This paper presents the mathematical modeling, analysis, and simulation results of a series-parallel hybrid electric vehicle (SPHEV). Detailed models of four main types of components—electric motor, internal combustion engine, battery, and auxiliary components—are presented, which can be used to model and simulate the drivetrain of full-electric, series hybrid, and parallel hybrid configurations. The simulation was performed using the graphical simulation language MATLAB/Simulink and is usable on most computer platforms.

KEY WORD- Battery management system, charging levels, electric vehicles (EVs), motor drive system.

1. INTRODUCTION

In recent years, soft computing technology has become a focus of research in the fields of computer engineering and automatic control, due to its advantages in dealing with ambiguity, uncertainty, and complex real-world problems. As a crucial development aspect of modern manufacturing industries, intelligent manufacturing requires robust identification capabilities. It is now widely accepted that a vehicle's fuel consumption is significantly affected by its operating environment. It is also well known that the impact of emissions is not only local but also affects the global climate. As a solution to this growing and now widespread problem, this report will propose an effective solution to reduce emissions and fuel consumption, thereby increasing overall efficiency. Compared to conventional vehicles, electric, hybrid, and fuel cell vehicles utilize more electrical components, such as electric machines, power electronics, electronic continuously variable transmissions (CVTs), and embedded powertrain controllers [1-3].

Next-generation powertrains include advanced energy storage devices and energy converters, such as lithium-ion batteries, ultracapacitors, and fuel cells. In addition to these electrical components or subsystems, conventional internal combustion engines (ICEs) and mechanical and hydraulic systems may also be present. The dynamic interactions between the various components and the multidisciplinary nature make analyzing a newly designed hybrid electric vehicle (HEV) challenging [4-5]. Each design parameter must be carefully selected for improved fuel efficiency, enhanced safety, exceptional drivability, and competitive dynamic performance at a price acceptable to the consumer market. Prototyping and testing each design combination is cumbersome, expensive, and time-consuming. Modeling and simulation are essential for the evaluation, prototyping, and analysis of HEV concepts. This is especially true when developing new hybrid powertrain configurations and controllers. Furthermore, the complexity of new powertrain designs and their reliance on embedded software are a cause for concern in automotive research and development efforts. This makes predicting the interactions between various vehicle components and systems increasingly difficult [6-7].

A hybrid electric vehicle (HEV) powertrain typically includes an energy storage system (ESS) and a traction electric motor in addition to the components found in a conventional powertrain. Efficiency improvements are achieved through downsizing the internal combustion engine (ICE), optimizing ICE operation, and regenerative braking. Increasing the ESS capacity of an HEV results in a drivetrain that relies heavily on the electric motor's traction power until its ESS is fully depleted. Such a vehicle can also be charged by plugging it into the grid. Once fully charged, an HEV primarily relies on its ESS module for the first few miles of its driving cycle. After that, it operates like a conventional HEV. The energy storage capacity of the ESS module in such an HEV is greater than that of existing HEVs, although it is not as large as the ESS modules used in electric vehicles (EVs). The performance of the ESS, which is composed of multiple battery modules, is therefore crucial in this context. The design parameters of an ESS module are discussed in [8-11].

Due to their flexibility in using chemical or electric fuels, HEVs are expected to have better fuel economy than conventional vehicles. HEVs can also be used as distributed energy storage (DES) units, which provide service to the grid while parked and plugged in. In this way, HEVs can be recharged at night (when the demand for electrical energy is low) and used as DES units during the day (when the demand for energy is high). This can help in peak load shaving of the grid [12-14].

However, to achieve these benefits, HEVs require high-capacity energy storage systems (ESS), and the vehicle must anticipate its driving patterns to avoid running out of energy required for propulsion. It is worth noting that the number of battery cycles of the ESSs associated with these vehicles is limited, and the DES activity for these vehicles should be managed in a way that adequately compensates for the loss of battery life due to the energy storage benefits provided to the consumer. Such high-capacity batteries or ESSs are expensive; this is the biggest obstacle to the mass production of HEVs [15-17].

The potential of applying soft computing technology in intelligent control for the transformation and modernization of the automotive industry has emerged due to their clean energy advantages. However, in the development of electric vehicles, the problem of optimizing their dynamic performance and economic performance together has become increasingly apparent [18]. Prioritizing dynamic performance often leads to a decrease in economic performance, while over-emphasizing economic performance may limit dynamic improvement. Therefore, maintaining a balance between these two aspects is a very important issue that needs to be addressed. New energy vehicles have been developed in response to the growing global concern about environmental protection, and their capabilities include reducing air pollution, alleviating the pressure caused by oil shortages, and protecting the environment by conserving energy and reducing emissions. The power system of an electric vehicle is crucial for enhancing its energy efficiency as an environmentally friendly transportation option [19]. However, optimizing the interaction and control strategies between components such as motors, battery packs, controllers, and transmissions remains a challenging problem. Traditional methods often fail to meet the specific requirements of electric vehicles, which requires new design and optimization methods to improve performance and reliability. As a result, researchers in related fields are increasingly focusing on the power system of electric vehicles.

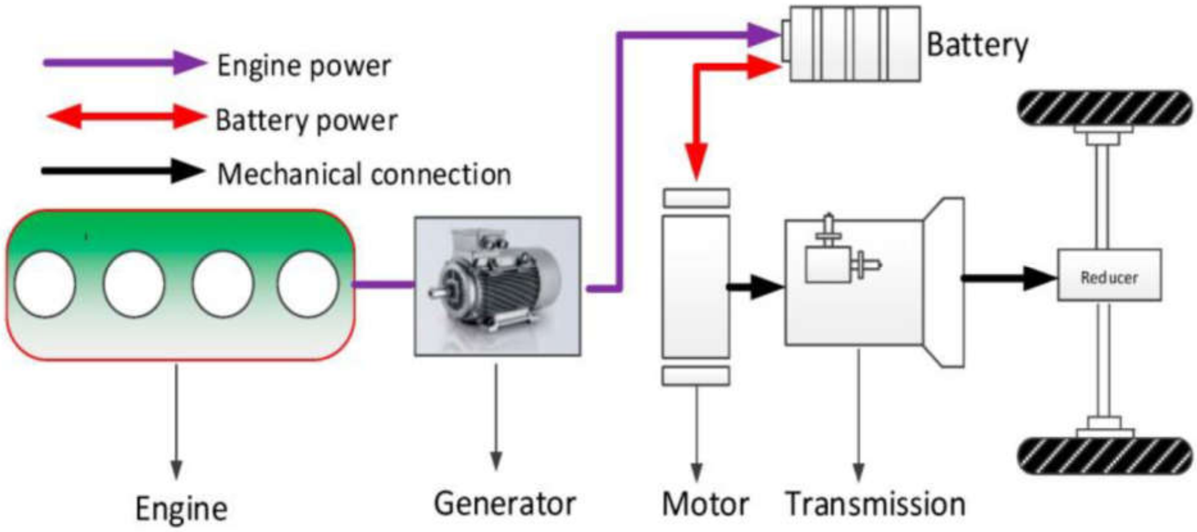

Figure 1. Diagram of Hybrid E-Vehicle

Simulation-based methods enable rapid optimization and the design of high-performance control strategies, provided that the accuracy of the simulation model and the reliability of the results can be ensured. Genetic algorithms (GAs), known for their powerful search and optimization capabilities, are being widely used in the optimization and control of complex systems and are yielding positive results. Applying GAs to the optimization of electric vehicle power systems helps in optimizing critical aspects such as battery capacity and motor control strategies, and also allows for complete adaptation to the specific requirements of electric vehicles [20-22].

2. LITERATURE REVIEW

Pormatin et al. (2023) reported that conventional methods for electric vehicle power system design and development have relied heavily on modeling, experience, and testing. While test-based methods offer higher accuracy and reliability, they are often costly and time-consuming, making it difficult to meet the demands of real-time and global power system optimization. Experience-based methods, relying on expert knowledge and data mining, are efficient and practical, but they lack systematicity and reliability. This application specifically enhances vehicle performance, driving range, and energy efficiency. Banani Ardekani et al. (2023) emphasized that accurate estimation of travel time information is one of the fundamental tasks of urban traffic control. Meanwhile, using multiple sensors simultaneously provides more accurate information for measuring traffic flow characteristics compared to using individual sensors alone.

In the field of soft computing for intelligent manufacturing systems, recent research has focused on the combined optimization of electric vehicle power performance and economic performance. Researchers are actively exploring various optimization methods and control strategies in computer engineering and automatic control to achieve optimal performance in electric vehicles. In particular, in the application of soft computing techniques, Genetic Algorithms (GA) have attracted considerable attention for addressing optimization challenges in electric vehicle power systems. Soft computing techniques are considered an effective way to solve complex optimization problems in intelligent manufacturing due to their ability to adapt to complex real-world problems. In the optimization of electric vehicle power systems, although conventional PID control methods and machine learning techniques have been widely studied, they fail to strike a balance between energy and economic performance. Consequently, researchers are increasingly turning to GA to achieve this balance, leveraging its capabilities for the combined optimization of electric vehicle dynamic and economic performance.

Tran et al. They have developed a hybrid electric vehicle that meets the performance criteria of the competition. Simulation results showed that the design model could meet the demands in terms of acceleration, braking, mileage, fuel efficiency, and emissions. In a review and analysis of research related to powertrain optimization for multi-speed discrete transmissions, continuously variable transmissions, and multi-motor configurations for electric vehicles, Majli et al. (2022) concluded that future advancements in electric vehicle technology may primarily focus on increasing powertrain efficiency and performance. Zhu et al. (2022) proposed a self-adaptive power-matching method using a deep deterministic gradient strategy. The results indicate that this method can provide longer battery life and lower energy consumption than expected. Mao et al. (2022) used Modelica for modeling energy systems, motor systems, and mechanical components and presented a modeling method for the drive system of an electric tractor. The results supported the validity of the simulation and the accuracy of the model, laying the foundation for future agricultural machinery research and development. Their findings demonstrated the accuracy of the simulation, establishing a foundation for future research and development in the field of agricultural machinery. Certainly, many researchers are optimizing power systems and resources using advanced algorithms.

Ali et al. (2021) significantly improved the performance of electric vehicle power systems by proposing a robust linear parameter varying control tuned by a GA for energy consumption optimization. Based on edge computing, Lv and Qiao (2020) presented an optimal edge server resource deployment scheme. Their research showed that collaborative optimal resource allocation is achievable through the strategic deployment of edge servers.

Eckert et al. (2022) used an interactive adaptive weighted GA to optimize the powertrain and control of a series electro-hydraulic hybrid electric vehicle. The research results showed that the high power density of the hydraulic accumulator effectively reduces battery degradation and acts as a peak power buffering unit. Leise et al. (2022) applied a multi-island GA to determine the transmission ratio and other critical parameters for the collaborative operation mode of a hybrid energy storage system based on a conventional energy management strategy and an equivalent minimum fuel consumption strategy for the auxiliary power plant. The results showed increased fuel efficiency and reduced battery degradation in the optimized operation mode. From the research and analysis of the above researchers, it can be seen that despite extensive research on the optimization and energy management of electric vehicle power systems, there are still some unresolved issues, such as balancing the overall power performance and economic performance of electric vehicles. Therefore, this research introduces a GA for algorithm optimization and applies it to the optimization of electric vehicle power systems. In the later stages, the optimization of the electric vehicle power structure can greatly benefit from this. With the continuous development of intelligent manufacturing technology, electric vehicles are a key component of intelligent transportation. Furthermore, optimizing its power system is crucial for realizing efficient, intelligent, and sustainable transportation. The application of soft computing technologies provides a novel concept and methodology for improving the power systems of electric vehicles.

The electric motor serves as the primary power source for electric vehicles, providing maximum torque output below its base speed and constant torque output at low speeds. It also offers the advantage of stable power output at high speeds and can operate at constant power above the base speed. Parameters such as acceleration, climbing ability, and other operational requirements determine the design criteria for selecting key components of the power system, such as the engine, drive motor, power battery, and front and rear axle retarders. This approach ensures that the electric vehicle's power source is better matched to the driving conditions and operates within a high-efficiency range to improve energy management strategies. Consequently, it provides an optimal high-efficiency range for energy management strategies, which is essential for increasing the vehicle's fuel efficiency and reducing emissions.

3. HYBRID ELECTRIC VEHICLE

The design may also include a generator between the power splitter and the battery, which helps to feed more power back into the battery. Conceptually, a hybrid electric vehicle combines the characteristics of an electric vehicle and an internal combustion engine (ICE) powered vehicle. At low speeds, it operates like an electric vehicle, with the battery supplying the driving power. At higher speeds, the engine and battery work together to meet the power demands. The sharing and distribution of power between these two sources is a key factor in fuel efficiency. It is worth noting that many other designs are possible, as the power sources can work together in various ways to meet the overall power demand.

4. DESIGN STEPS

The fundamental challenges in hybrid electric vehicle (HEV) design are similar to those in traditional engineering, involving complexity across different levels and domains, and requiring coordination between various factors. Here, we will briefly discuss the key aspects of component design:

4.1 Engine design

The main components of the engine design are similar to those of traditional internal combustion engines (ICE). The engines used in hybrid electric vehicles are typically smaller than the conventional engines of similarly sized cars, and their size is selected based on the overall power requirements of the vehicle.

4.2 Battery Design

Due to their superior energy and power density, lithium-ion batteries are currently considered the best option for energy storage in electric vehicles compared to lead-acid or nickel-metal hydride batteries. The battery model used in this work is based on the A123 Systems high-performance lithium-ion cell ANR26650MI. This battery exhibits excellent energy density, high efficiency, and lower cost compared to batteries used in previous vehicle studies. The total resistance and %V-SOC curve depend on two variables: the number of cells in series and parallel (batt_s and batt_p). The %V-SOC curve is a function of the percentage of maximum voltage, similar to a fuel cell model, allowing it to be applied to cells with different serial numbers. The estimated efficiency is 95%. The main considerations in battery design are capacity, discharge characteristics, and safety. Traditionally, higher capacity is associated with larger size and weight. The discharge characteristics determine the dynamic response of the electrical components when drawing or supplying power from the battery.

4.3 Motor

The motors commonly used in HEV systems are DC motors, AC induction motors, or permanent magnet synchronous motors (PMSMs). Each motor has its own advantages and disadvantages, which determine its suitability for a particular application. Of these, the PMSM has the highest power density, while the DC motor has the lowest.

4.4 Power Splitter

A planetary gear set is an efficient power splitter that allows power to flow from two power sources to the driveshaft. The engine is typically connected to the sun gear, while the motor is connected to the ring gear.

5. MODELLING

A hybrid energy storage system (HESS) consists of a supercapacitor, a Li-ion battery, and a PEMFC. These three sources are often used in FCHEVs to ensure that the load receives sufficient and reliable power. This system has three power sources: a capacitor, a fuel cell, and a rechargeable battery. The fuel cell is equipped with a DC/DC boost converter that increases its voltage level to the desired level and maintains it at the output. The battery has a DC/DC bidirectional power supply device that converts the varying power to a fixed voltage. The supercapacitor is integrated into a bidirectional converter, which, like some other capacitors, allows for energy exchange in both directions.

DC-to-DC converters transform one level of DC voltage to another. The operating voltage of various electronic devices, such as ICs and MOSFETs, can vary over a wide range, making it necessary to provide the correct voltage for each device. A buck converter provides a voltage output lower than the original voltage, while a boost converter supplies a higher voltage. The efficiency, ripple, and load-transient response of a circuit can be modified using DC-to-DC converters. The best external parts and components usually depend on the operating conditions, such as the input and output specifications. Therefore, when a product is designed, standard circuits must be modified to suit their specific needs and different specifications. Designing a circuit that meets all specifications and requirements requires considerable expertise and experience in this field. Step-up or step-down DC-to-DC converters are useful in applications where the battery voltage may be higher or lower than the regulator output voltage. The DC-to-

DC converter must be capable of operating as a step-up or step-down voltage supplier to provide a constant load voltage across the entire battery voltage range during operation.

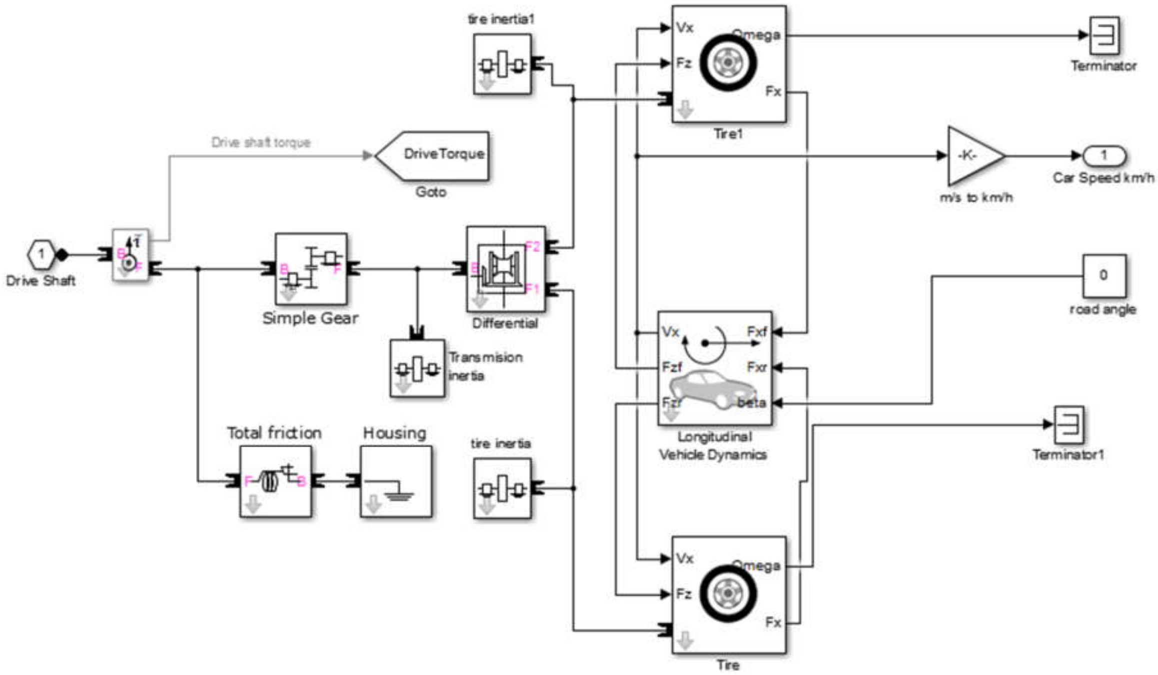

Figure 2. Hybrid Electric Vehicle Dynamic System

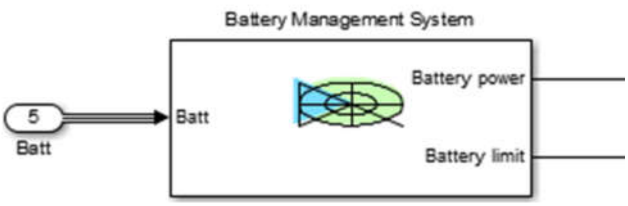

Figure 3. Battery Management System

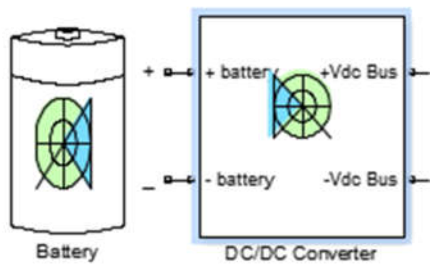

Figure 4. Energy storage system with DC/DC Converter

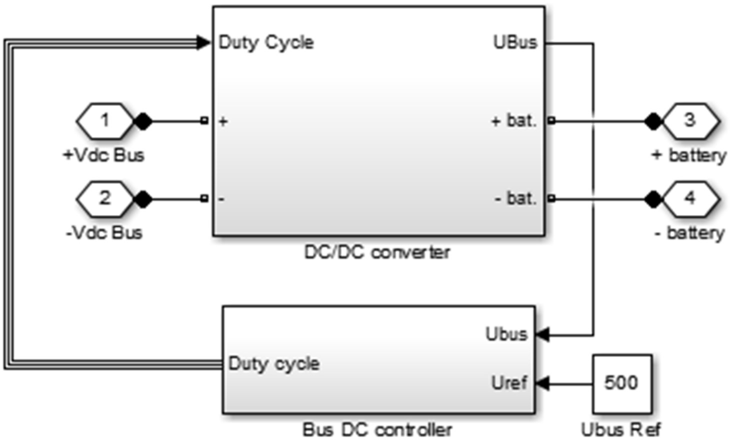

Figure 5. DC/DC Converter

6. RESULTS AND DISCUSSION

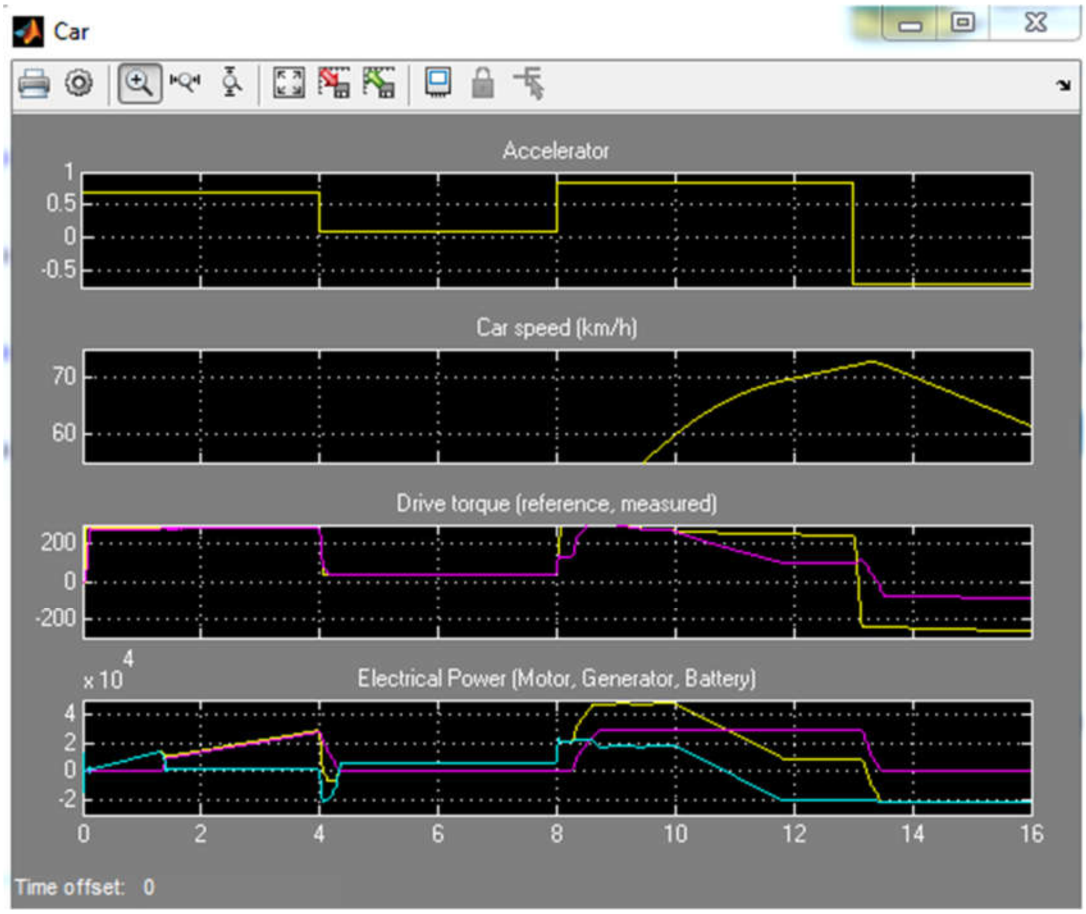

Figure 6. Accelerator, Car Speed, Drive Torque and Electrical Power

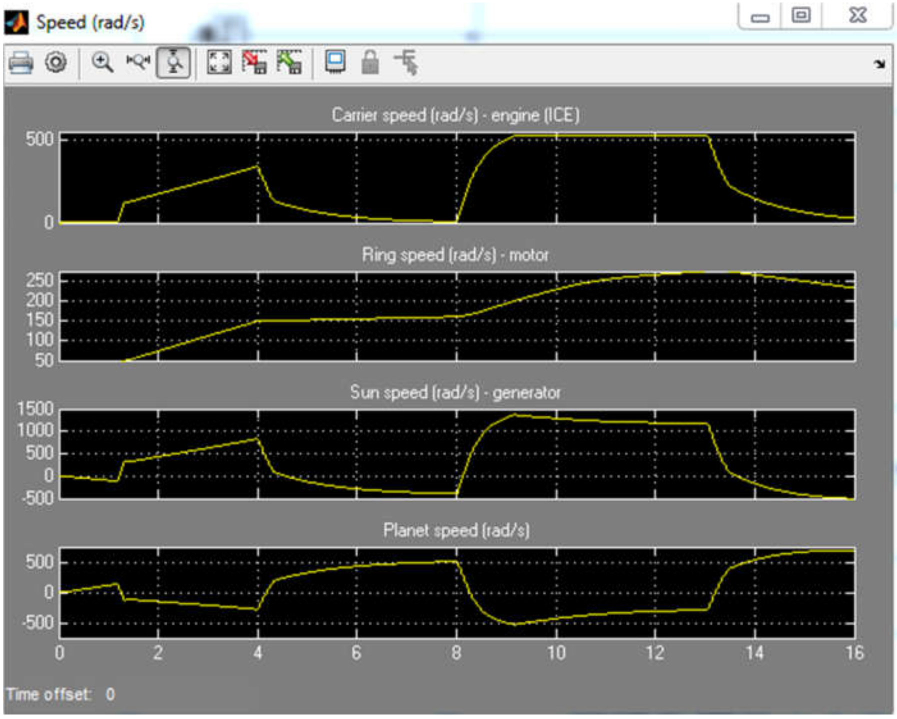

Figure 7. Carrier speed, Ring speed, Sun speed and Planet Speed

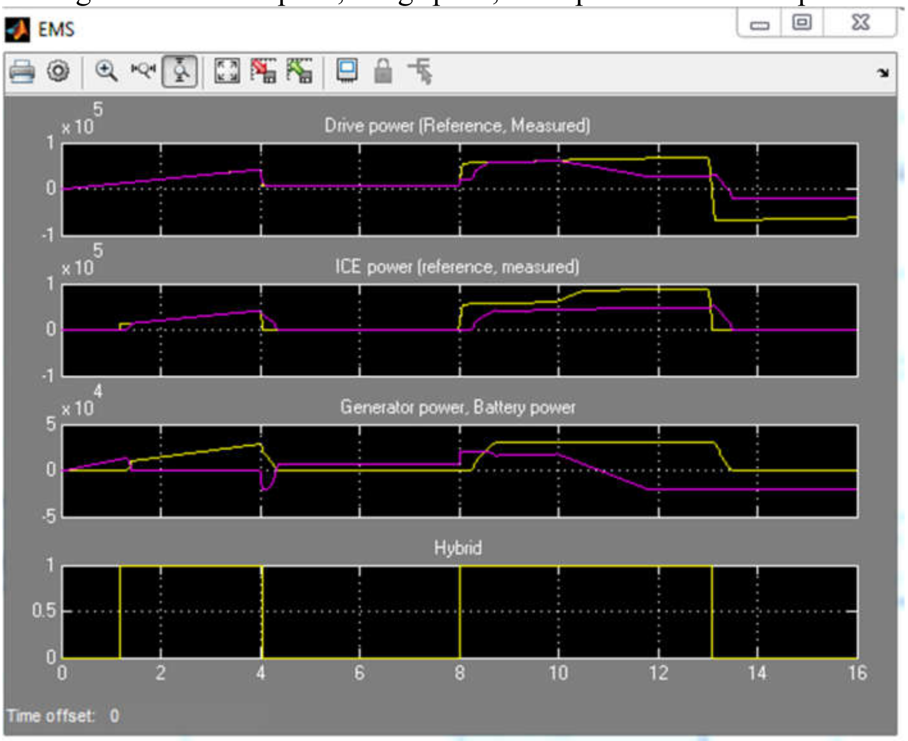

Figure 8. Drive Power, ICE Power, Generator Power, Battery Power and Hybrid

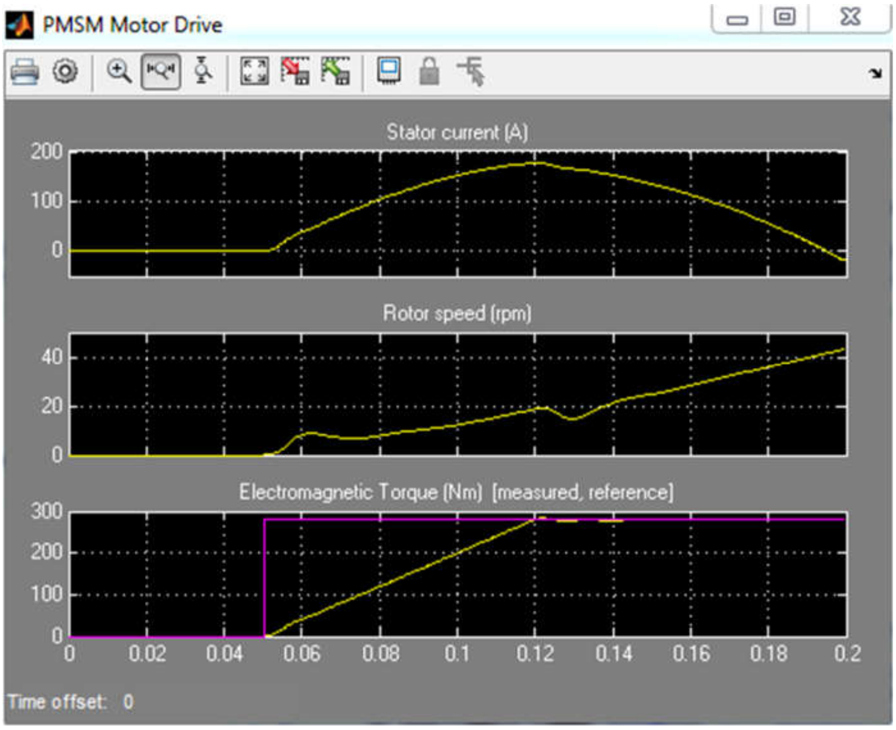

Figure 9. PMSM Motor Drive of Stator Current, Rotor Speed and Electromagnetic Torque

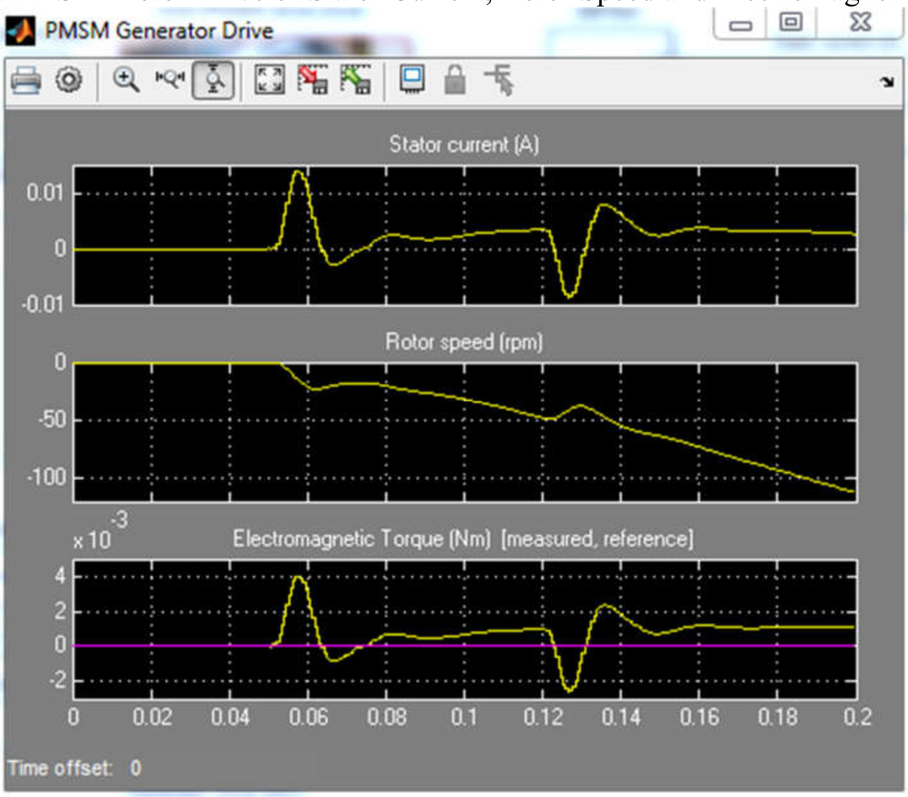

Figure 10. PMSM Generator Drive of Stator Current, Rotor Speed and Electromagnetic Torque

1. This HEV has two types of motive power sources: an electric motor and an internal combustion engine (ICE), to increase drivetrain efficiency and reduce air pollution.
2. The electric motor is a 500 V dc, 50 kW interior permanent magnet synchronous machine (PMSM) with an associated drive. This motor has 8 poles and the magnets are internally mounted (salient rotor type). Flux weakening vector control is used to achieve a maximum motor speed of 6000 rpm.
3. The generator is a 500 V dc, 2-pole, 30 kW PMSM with an associated drive. Vector control is used to achieve a maximum motor speed of 13000 rpm.
4. The battery is a 7.5 Ah, 220 V dc.
5. The DC/DC converter (boost type) is voltage regulated. The DC/DC converter adjusts the battery's low voltage (200 V) to the voltage of the DC bus, which powers the AC motor at a voltage of 500 V.

The planetary gear subsystem models the power split device. It uses a planetary device that transmits, splits, and combines mechanical motive force from the engine, motor, and generator. It represents a set of carrier, ring, planet, and sun gears that control the connected driveline axes. The gear ratio is the ratio of the gear teeth (the ratio of the gear radii). The ring and sun rotate together in opposite directions relative to the carrier at a fixed gear ratio. The ring-sun gear ratio must be strictly greater than one. The internal combustion engine subsystem models a 58 kW @ 7000 rpm gasoline fuel engine with a speed governor. The throttle input signal is between zero and one, and it represents the requested engine torque as a fraction of the maximum possible torque. This signal also indirectly controls the engine speed. The engine model does not include air-fuel combustion dynamics.

The vehicle dynamics subsystem models all the mechanical parts of the vehicle:

1. A single reduction gear reduces the motor speed and increases the torque.
2. The differential splits the input torque into two equal torques for the wheels.
3. Tire dynamics represent the forces exerted on the ground.
4. Vehicle dynamics represent the effect of motion on the entire system.
5. A viscous friction model represents all the losses occurring in the mechanical system.

7. CONCLUSIONS

This article describes the modeling and control of a series-parallel hybrid electric vehicle (HEV), with a particular focus on modeling. Simulation results for the vehicle and electrical subsystems are presented. It is concluded that due to stringent constraints on energy resources and environmental concerns, hybrid electric vehicles will attract significant attention from the automotive industry and consumers. Modeling and simulation will play a crucial role in the success of hybrid electric vehicle design and development. In this article, we have discussed powertrain modeling, simulation, and analysis using MATLAB/Simulink software to study issues related to electric vehicle and hybrid electric vehicle design such as energy efficiency, fuel economy, and vehicle emissions. This software utilizes visual programming techniques, allowing the user to quickly modify its structure and parameters and visualize the output data graphically. It also includes detailed models of the electric motor, internal combustion engine, and battery. A specific configuration has been considered, where the electric motor is placed between the internal combustion engine and the gearbox, with a six-speed gearbox. A simple control strategy has been implemented to manage the power flow between the internal combustion engine and the electric motor, and an optimization process has been used to obtain the control parameters. Simulation results such as fuel consumption, vehicle emissions, and the complexity of each vehicle have been compared and discussed.

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