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**INTELLIGENT ENERGY MANAGEMENT IN A TWO POWER-BUS
VEHICLE SYSTEM**

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ABSTRACT

In this paper we present an intelligent power controller for a vehicle power system that employs multiple power sources. In particular we focus on a vehicle power system architecture that is used in vehicles such as Mine Resistant Ambush Protected (MRAP) vehicle. These vehicles are designed to survive IED (Improvised Explosive Devices) attacks and ambushes. The power system has the following major components: a “clean” bus, a “dirty” bus, an engine, a hydraulic system and a switch between the clean and the dirty bus. We developed algorithms for intelligent energy management for this type of vehicle power system including DP (Dynamic Programming) optimization, DP online control and a machine learning technique that combines neural networks with DP to train an intelligent power controller. We present experiments conducted through modeling and simulation using a generic commercial software tool and a lab hardware setup.

INTRODUCTION

The automotive industry is facing increased challenges of producing affordable vehicles with increased electrical/electronic components in vehicles to satisfy consumers' needs. At the same time these vehicles should have improved fuel economy and reduced emission without sacrificing vehicle performance, safety, and reliability. In order to meet these challenges, it is very important to optimize the architecture and various devices and components of the vehicle system, as well as the energy management strategy that is used to efficiently control the energy flow through a vehicle system [1, 2]. Our research focuses on the later [3 ~ 5]. Vehicle power management has been an active research area in the past decade. The traditional power management approaches were developed based on mathematical models or human expertise based on efficiency maps or knowledge derived from simulation data. Those traditional approaches have been applied to commercial vehicles [6].

Unlike conventional vehicles, military vehicles have characteristics such as multiple power sources, complex configuration and operation modes. In addition, most military vehicles are heavy weight, and have more functions like engaging weapons, turning on sensors, silent watch, etc., resulting in bigger load fluctuations which require a more advanced power control strategy. Therefore, the power control strategies in conventional vehicles do not meet the requirements for the power control of military vehicles.

We are conducting research in Cognitive Intelligent Vehicle Power Management, which is a power management approach that provides intelligent power control based on machine learning, optimization, and human intelligence. This approach provides the potential of fuel efficiency and high reliability in vehicle operation resulting in higher probability of mission success.

In this paper we present an intelligent power controller developed for a vehicle power system that employs multiple power sources. In particular we focus on a vehicle power system architecture, Mine Resistant Ambush Protected (MRAP) vehicle [7]. These vehicles are designed to survive IED (Improvised Explosive Devices) attacks and ambushes.

The power system has the following major components: a "clean" bus, a "dirty" bus, an engine, a hydraulic system and a switch between the clean and the dirty bus. The clean bus may contain loads like electronic equipments that require more precisely controlled power source, when compared to the dirty load, which may have motor loads, not requiring very precise power source control. Both buses have the same topology.

We developed power flow control algorithms that intelligently control the battery power in the dirty bus. Three algorithms are presented in this paper, Dynamic Programming (DP), DP online control, and an intelligent controller, which is a machine learning technique that combines neural networks with a DP power optimization. The experiments have been conducted through modeling and simulation using a generic commercial software tool and a lab hardware setup to test our power management algorithms.

Based on the power flow shown in Fig. 1, we developed three algorithms for intelligent energy management for this type of vehicle power system, DP (Dynamic Programming) optimization, DP online control and a machine learning technique that combines neural networks with DP to train an intelligent power controller. We present experiments conducted through modeling and simulation using a generic commercial software tool and a lab hardware setup.

This paper is organized as follows. Section 2 presents the vehicle power system in a two power-bus model. Section 3 introduces the intelligent power management algorithms used in the vehicle systems, Section 4 presents our experiment results and Section 5 concludes the paper.

A vehicle power system in a two power-bus model (MRAP model)

In this paper, we focus on the energy optimization in the vehicle systems that have the power system shown in Fig. 1. The power system has the following major components: clean bus, dirty bus, engine, hydraulic system and a switch between the clean bus and dirty bus. This type of power system has been proposed in some military armored fighting vehicles such as MRAP vehicles that are designed to survive IED attacks and ambushes.

The clean bus may contain loads that are steady but small in power consumption when compared to the dirty load, which may have inductive loads. Both buses have the same topology. The clean bus is connected to the alternator run by a hydraulic pump/motor system. The dirty bus is with the alternator directly connected to the engine. The clean and dirty buses do not communicate to each other. Only when the dirty bus battery is running low, the driver can connect the dirty bus manually to the clean bus battery by turning on the switch, which is meant to help the start of the starter motor (which is connected to the dirty bus).

The clean and the dirty buses are just left on their respective alternators for charging. The alternators have regulators which are set at certain values. Regulators try to maintain the voltage, and in the process the batteries can get charged or not. The hydraulic system keeps its speed fixed over the wide range of engine speed fluctuation, both from idle to higher engine speeds.

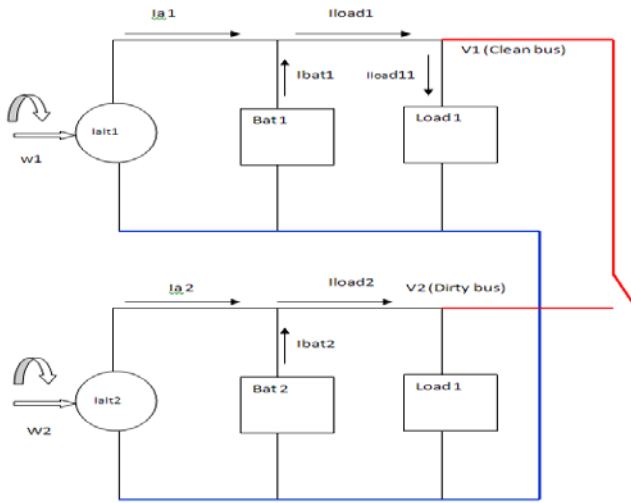


Fig. 1. Power system in a two power-bus model

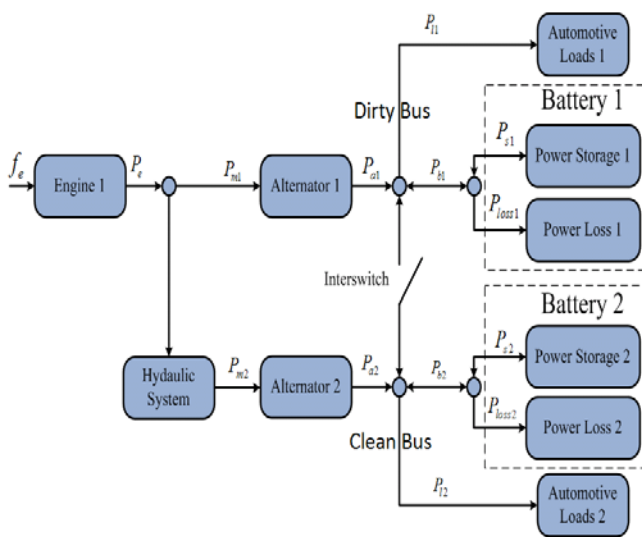


Fig. 2: Power flow in a two power-bus system.

Intelligent power management in vehicle systems of two power buses

We model the power management problem as an optimization process based on the power flow shown in Fig. 2. For a given drive cycle, $DC(k)$, $k = 1, \dots, N$, the objective function for optimizing fuel consumption is defined as follows:

$$\min J = \min_{P_s} \text{fuel}(P_e) = \min_{P_s} \sum_{k=1}^N \text{fuel_rate}(P_s | DC(k)) \quad (1)$$

where P_e is the engine power, P_s (i.e. P_{s1} in Fig. 2) is the battery power in dirty bus, fuel_rate is the rate of fuel consumed during the given drive cycle $DC(k)$, and is a function of engine speed and engine power requested during the drive cycle. A drive cycle, $DC(k)$ is a vehicle speed function at discrete time steps. For the power system shown in Fig. 2, the control variable is the battery power, P_{s1} , in the dirty bus. Once the optimal points of P_{s1} are obtained, optimal engine power can be obtained through the power flow shown in Fig. 2.

We developed three algorithms for intelligent power management. First, we applied the dynamic programming algorithm (DP) to training drive cycles to find the optimal values of the control variable, P_{s1} , while satisfying all system constraints. The second algorithm is to apply the optimal power setting found by DP to a vehicle model to evaluate the online performance. This process is referred as online open loop DP. Ideally, the open-loop DP should have the same performances as the offline DP. However, due to the vehicle dynamics, the open-loop DP often does not perform as good as the offline DP program. Third, we developed an intelligent power control that contains neural networks (NNs) that are trained to (1) predict roadway types in real world driving, and (2) generalize the optimal power settings generated by DP, so the online intelligent controller with these neural networks can generate optimal power settings during real time vehicle drive cycles.

The online intelligent controller has two major computational steps. At every time instance during a real time drive cycle, the intelligent controller first calls the roadway prediction neural network to obtain the current roadway type. It then calls the power neural networks trained for the current roadway type to generate the optimal power for P_{s1} .

In order to evaluate the intelligent controller performances for a MRAP vehicle, we constructed a special drive cycle that is close to its operational environments. The drive cycle consists of three types of roadways, typical for heavy trucks, WVU_City, WVU_Suburban and WVU_Interstate (West Virginia University Cycles) and 70% of it is in the silent mode, i.e. speed is zero. The entire cycle, illustrated in Fig. 3, has 2000 seconds. A neural network, NN_{rt} , is trained to predict the current roadway types based on the vehicle's recent speed. Dynamic Programming is applied to each of the three roadway types to generate optimal power settings. Three power neural networks, one for each roadway type, were trained to generate optimal battery power settings based on the DP output.

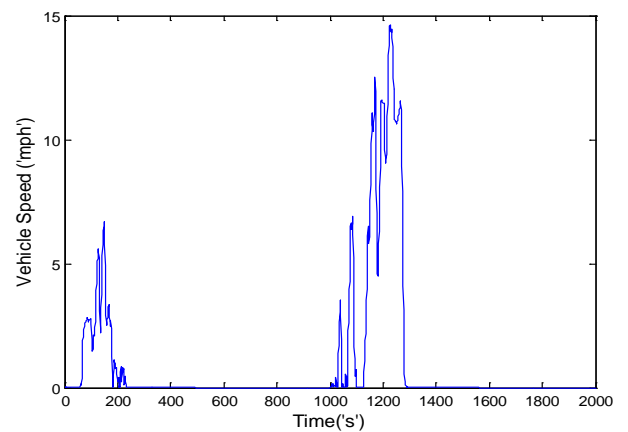


Fig. 3. A test drive cycle

Experiments

Based on the specification of the vehicle model shown in Fig. 1, we built a simulation program to study energy

optimization in multi-power vehicle systems. We also implemented the power system of MRAP in hardware in a lab setting to demonstrate the effectiveness of the proposed energy management algorithms.

For simulation we build a full scale system model using a tool which is a high fidelity simulation software developed by Argonne National Laboratory with contributions from various automotive manufacturers. We developed the vehicle model by constructing the power components with the same sizes as in the specifications. Fig. 4 illustrated the full simulation model. We applied all three algorithms, the DP offline, open loop DP, and the intelligent controller to the simulated vehicle model for power control in the test drive cycle, and the performances are shown in Table 1. We can see the intelligent controller online control obtained really good performance, which is 5% saving compared to benchmark simulation.

The hardware MRAP power system, illustrated in Fig. 5, was built at the academia authors' Power Electronics Lab. It is a scaled-down version and is designed to demonstrate the effectiveness of the proposed intelligent controller. The system is constructed based on an electric machine subsystem, and a data control and acquiring system. In this hardware implementation, we used a motor to track the speed profile of engine, replaced the alternator with the DC field

excited generator, and use the Lithium-ion battery module. The control algorithms implemented here are based on a generic software control algorithm, the offline DP, and the intelligent controller algorithm.

The components of the dirty bus branch are the dc power supply, power inverter, induction motor, field controlled dc generator, batteries, electronic load, and sensors. In the clean bus branch, the subsystem contains same components as the dirty bus branch except for the replacement of hydraulic system is the Permanent Magnetic DC Motor. All the data acquisition and control algorithm implementation are realized using the lab bench real time environment.

In our experiments, the engine speed is strictly controlled according to the drive cycle demand, and based on the vehicle's default control algorithm and DP algorithm. Different experiments were carried out to validate our control algorithm. And all the data and control algorithm are realized through the lab bench real time environment.

The fuel consumptions of these controllers are shown in Table 2. The online intelligent controller was able to save 3.24% fuels, which is close to the upper bound of energy saving, 5.14%, which was generated by offline DP optimization program.

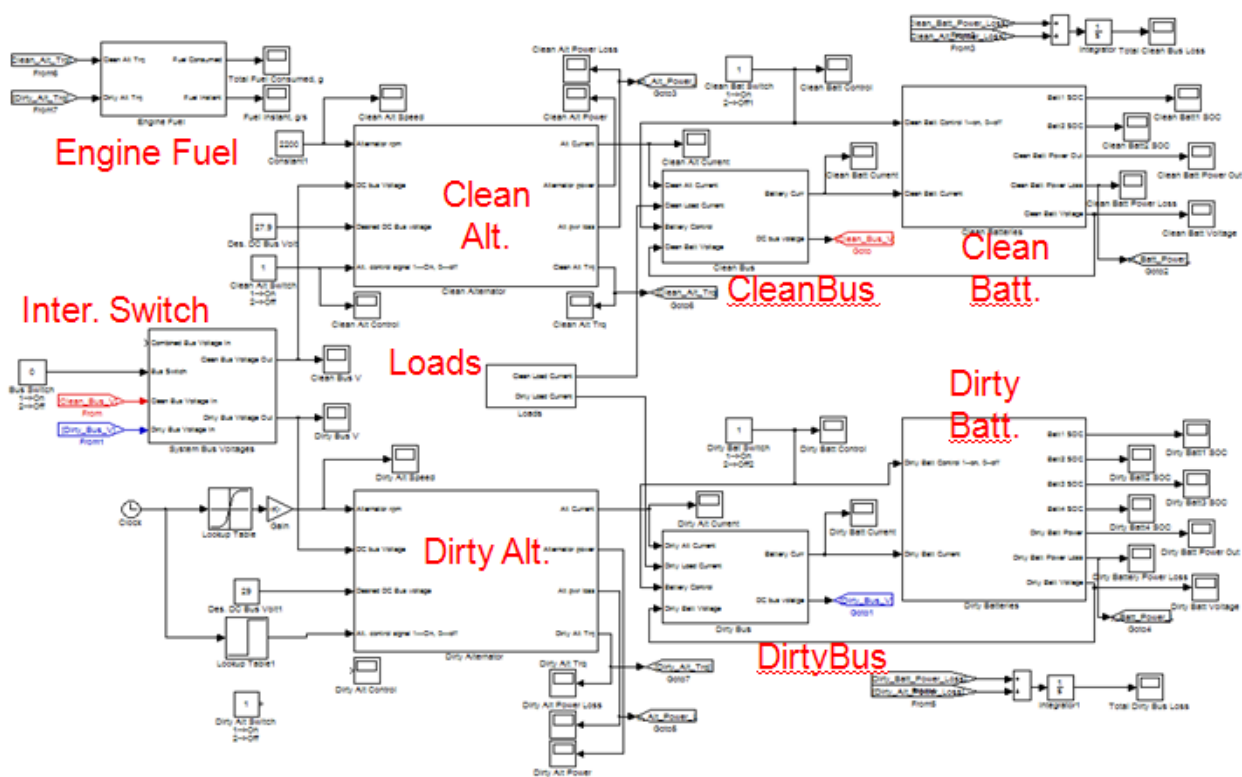


Fig. 4 MRAP Power System using commercial software tool.

Table 1. Performances of DP and Intelligent Power Controller (IPC, developed by the authors)

controller	Fuel Consumed (kg)	Fuel w/ SOC correction	Savings (%)
Generic simulation tool based controller	1.6920	1.6920	baseline
DP offline	1.5614	1.5614	7.72
Open-loop DP	1.6030	1.6100	4.85
Online IPC	1.5961	1.6074	5.0

Table 2. Fuel Consumption Comparison in a lab hardware setup

Algorithm	Fuel Consumption	Saving
Generic software tool based control algorithm	3.5336kg	baseline
DP offline Control	3.352kg	5.14%
Online IPC control	3.419kg	3.24%

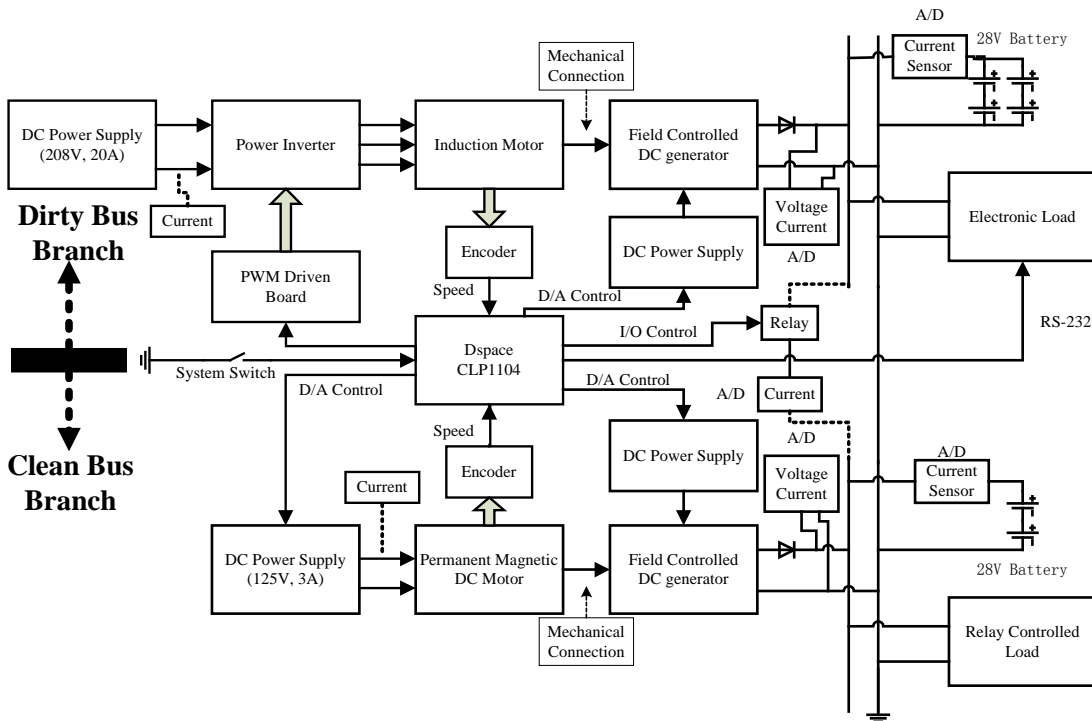


Fig 5. Hardware implementation

Conclusions

Simulation and scaled down models are excellent tools to develop and demonstrate the functionality of a vehicular power management system controller. This has been clearly shown through the work reported here. In particular, the work presented here showed the functionality of an intelligent power controller for a two power-bus system in vehicle systems. Based on the simulations, and experimental results implemented in the lab setup, it can be concluded that the intelligent controller developed by the authors can improve fuel consumption through online vehicular power management in a real time environment. In the simulated vehicular system, this controller saved about 5% fuel. In a lab setup environment, the controller saved about 3.2% fuel. The tools developed by the authors and reported in this paper can be used to save significant cost and development efforts by the manufacturers prior to any production level activities involving such vehicular systems.

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