2022-01-0352 Published 29 Mar 2022

A Prognostic Based Control Framework for Hybrid Electric Vehicles

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Citation: Hoang, P.H., Ozkan, G., Badr, P., Timilsina, L. et al., "A Prognostic Based Control Framework for Hybrid Electric Vehicles," SAE Technical Paper 2022-01-0352, 2022, doi:10.4271/2022-01-0352.

Received: 24 Jan 2022 Revised: 24 Jan 2022 Accepted: 13 Jan 2022

Abstract

Electrified transportation has received significant interest recently because of sustainable and clean energy goals. However, the degradation of electrical components such as energy storage systems raises system reliability and economic concerns. In this paper, a prognostic-based control strategy is proposed for hybrid electric vehicles (HEVs) to abate the degradation of energy systems. Degradation forecasting models of electrical components are developed to predict their degradation paths. The predicted results are then used to control HEVs in order to reduce the degradation of components.

Introduction

Electrified transportation is widely considered the future of transportation. However, there are still limitations in adopting electrified vehicles. Some of those limitations are energy storage (ES) costs, charging issues, and the reliability of electricity sources during operation. Out of the mentioned reasons, the first one is considered one of the main reasons making electrified vehicles less competitive compared to gasoline-powered vehicles. It is estimated that in average, the cost of battery accounts for 30% of an electric vehicle (EV) as of 2020 [1] that it raises concerns about the economic competitiveness of electrified vehicles. Therefore, reducing the degradation costs can accelerate the adoption of electrified transportation.

Literature Review: Hybrid electric vehicles (HEVs) are still being developed along with EVs because of the existing limitations of EVs. In an HEV, multiple energy sources are deployed to power the vehicle. Typically, an HEV will contain an internal combustion engine (ICE) system and one or more energy storage systems (ESSs) [2]. ESSs could be batteries or fuel cell systems. With multiple energy sources, it demands energy management (EM) to optimally allocate power to energy sources. Saving fuel consumption is mainly considered in the objective function of EM [3, 4]. Properly controlling HEVs can reduce their components' degradation. In [2], it is reported that the degradation of a battery in a hybrid ESS depends on the EM's strategies. This behavior can be reasoned that EM decides the energy generation to energy sources; it decides their operating conditions. In fact, in the literature, it has been reported that the degradation of a battery depends on its operating conditions such as working temperature, charge, and discharge currents. Therefore, it is reasonable to include operating conditions into electrical components' degradation models.

In order to have proper control strategy, degradation forecasting strategies play an important role. As a consequence, there are various works on the battery degradation model topic, [5, 6], to name just a few. In [5, 6], statistical models are used to model battery degradation. As mentioned earlier, operating conditions impact the degradation processes of an engineering system. However, statistical models which does not include future operating conditions may not work well for the case of HEVs as their working conditions varies.

Health monitoring for engineering systems also gains interest from the industry. In [7], a software platform called Maintenance Aware Design environment (MADe) is presented. The platform can be applied to various engineering systems. However, the idea of integrating degradation forecasting into realtime control and management of HEVs is a newly adopted concept, especially integration degradation forecasting with realtime EM.

Statement of Contributions: In this paper, we proposed a prognostic-based control strategy for HEVs. A load dependence model is used to model components' degradation. The predicted results are used to adjust EM's configurations to abate the degradation of degraded components. In doing so, the degradation of degraded components is abated while systems' functions are ensured. A numerical simulation shows that the cost of operating vehicles is reduced.

Paper Organization: The remainder of this paper is summarized as follows. In the next section, the powertrain model used in this paper is presented. Then, the hierarchical control architecture of the model is described. Next, A degradation modeling and forecasting model is discussed. A prognostic-based control strategy is proposed and validated by numerical simulations. Conclusion and future work ends this paper.

Hybrid Electrical Powertrain Model

It is noted that there are various HEVs' powertrain configurations. In addition, different configurations have different control strategies. In this paper, the powertrain model illustrated in Figure 1 is investigated. Applications of this design are heavy-duty vehicles.

The model has a 600 VDC bus powered by an internal combustion engine (ICE) and an ESS. As can be seen, energy sources and loads are decoupled from the bus by power electronics converters interface. This design is economically feasible because of recent advancements in power electronics and the reduction in power electronic device costs. Because of the decoupling, the implementation of EM is eased as the issues of power split in HEVs are relaxed. In particular, by this design, various constraints in EM due to the dynamics of propulsion loads and the internal combustion engine (ICE) can be relaxed.

It is also noted that this design also allows the vehicle to grid (V2G) mode and the vehicle to vehicle (V2V) mode. Therefore, the design contains a V2X outlet.

Hierarchical Control Architecture

The reduction in computational devices' cost and the improvement of their capabilities allow a wide deployment of computational devices into vehicles. Consequently, it eases the adoption of computational demanding algorithms and strategies in order to operate vehicles efficiently. Optimization and forecasting functionalities are of those. A hierarchical control strategy is introduced in this section and illustrated in Figure 2. The cost reduction and enhanced capacities enable this design.

FIGURE 1 HEV powertrain configuration considered in this paper.

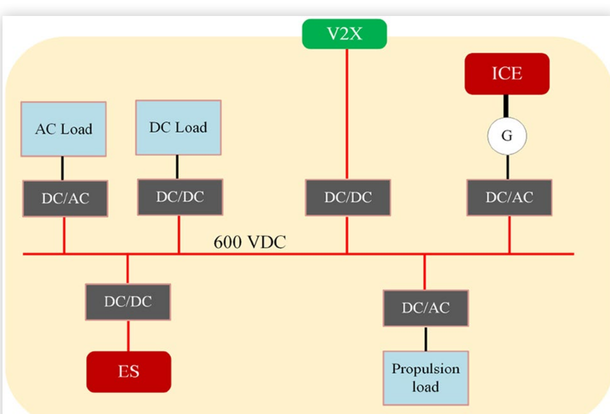
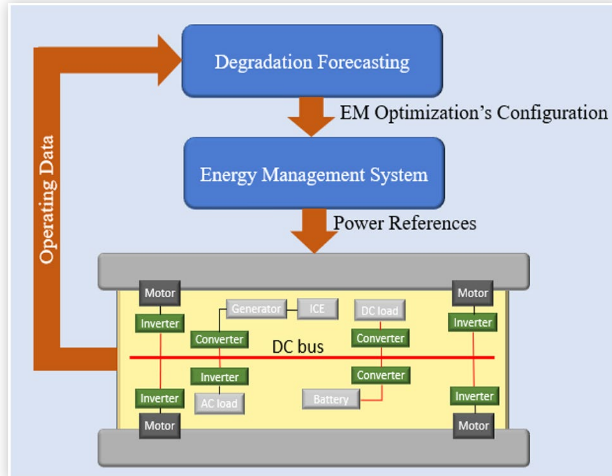


FIGURE 2 Hierarchical control architecture.



First, the design contains an energy management (EM). EMs have been widely deployed into vehicles for fuel savings purposes. It is noted that different powertrain configurations may have different optimization formulations for EM, and thus different strategies. With the HEV illustrated in Figure 1, the optimization of EM can be presented in a general manner as

$$\min \sum_{s \in \mathcal{S}} f_s\left(P_s\left(t_k\right)\right) \tag{1a}$$

$$P_s\left(t_k\right) \in \mathcal{P} \tag{1b}$$

$$\mathbf{x}_s\left(t_k\right) \in \mathcal{X} \tag{1c}$$

where t_k is the time instant in the discrete domain, $\mathcal{S}$ is the set of indices of energy sources, and $P_s(t_k)$ is power generated by source s at t_k, $\mathbf{x}_k(t_k)$ is the set of states of system s, and $\mathcal{P}$ and $\mathcal{X}$ are correspondingly the constraints set of $P_s(t_k)$ and $\mathbf{x}_k(t_k)$. For the sake of presentation, t_k is omitted.

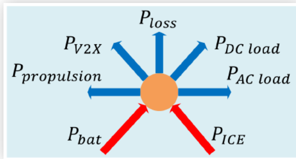
Next, the details of EM's optimization problem formulation are discussed. Typically, the EM's optimization problem mainly considers fuel cost savings. However, the degradation of electrical components becomes an issue and adds up to the cost of vehicles' operations, especially batteries, as it is mentioned earlier that batteries account for 30 % of vehicles' cost on average. Therefore, degradation costs should be taken into account. However, determining appropriate degradation costs is challenging. There are works that simply add a constant to the total cost function, i.e., (1a). However, the degradation of a component depends on its conditions and its operating conditions

Any energy source has generation capacity limits. Therefore, one of the constraints of (1b) is lower and upper generation limits as

$$\underline{P_{bat}} \le P_{bat} \le \overline{P_{bat}} \tag{2a}$$

$$\underline{P_{ICE}} \le P_{ICE} \le \overline{P_{ICE}} \tag{2b}$$

FIGURE 3 Power flow model.



The primary goal of powertrains is supplying loads properly. That is, the total generation should be met the total load and any losses. With the considered configuration, the following constraint is formed.

$$P_{bat} + P_{ICE} = P_{AC\,load} + P_{DC\,load} + P_{propulsion} + P_{V2X} + P_{loss} \tag{3}$$

where P_{bat} is power generated by the battery, P_{ICE} is power generated by the ICE, $P_{AC\ load}$ is AC load, $P_{DC\ load}$ is DC load, $P_{propulsion}$ is propulsion load, P_{V2X} is power used for V2X mode, and P_{loss} is the total loss. This constraint is illustrated in Figure 3.

Each system has internal constraints, i.e., (1c). The following constraints are considered for the battery and the ICE.

$$\left|\left(P_{ICE}\left(t_{k+1}\right) - P_{ICE}\left(t_k\right)\right)\right| < rr_{ICE} \tag{4a}$$

$$\left|P_{bat}\left(t_{k+1}\right) - P_{bat}\left(t_k\right)\right| < rr_{bat} \tag{4b}$$

$$\underline{SoC_{bat}} \le SoC_{bat} \le \overline{SoC_{bat}} \tag{4c}$$

$$SOC_{bat}\left(t_{k+1}\right) = SOC_{bat}\left(t_k\right) - \frac{\delta T i_{bat}}{Q_{nom}} \tag{4d}$$

where $\delta T = t_{k+1}$ - t_k. Constraints (4a) and (4b) are understood both the battery and the ICE have ramp rate limits when adjusting their generation. Constraints (4c) and (4d) are the battery's State of Charge (SoC) constraints.

Degradation Modeling and Forecasting

The degradation models are constructed to predict the degradation paths. It is reasonable to assume that the degradation of a component is impacted by its working conditions. This assumption is verified by examining the Short-Term Cycling Performance Dataset dataset from Sandia National Laboratories. As can be seen in Figures 4 and 5, temperature and discharge/charge current have impacts on battery degradation.

Given the above observations, a load dependent degradation model is used. A Markov chain based model of 4 states is constructed to forecast the degradation process of a component [8]. The Markov model transitioning $\mathbf{x}_n$ at time t_k to $\mathbf{x}_n$ at time t_{k+1}, which is illustrated in Figure 6 b), has the following formula:

FIGURE 4 Impact of temperature on battery degradation.

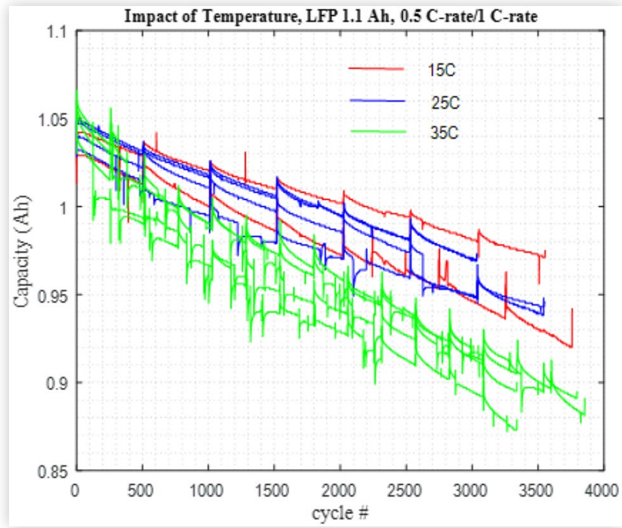
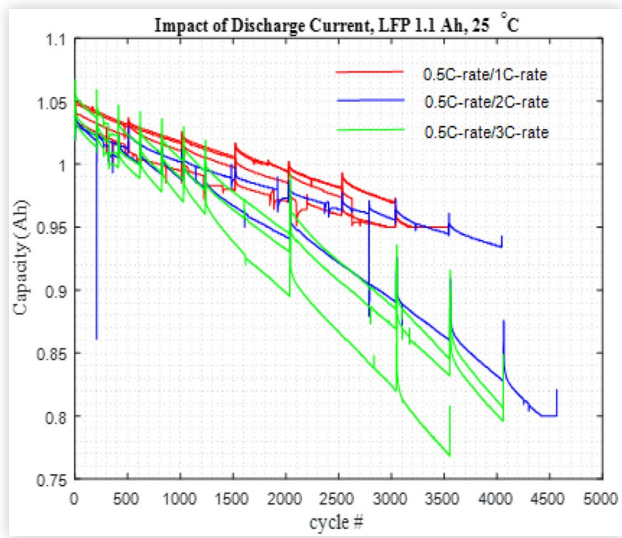


FIGURE 5 Impact of discharge/charge current on battery degradation.



$$\mathbf{x}\left(t_{k+1}\right) = \mathbf{x}\left(t_k\right)\mathbf{T} \tag{5}$$

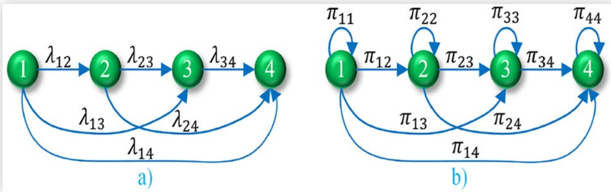
where $\mathbf{T}$ is the transition matrix

$$\mathbf{T} = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} \end{bmatrix} \tag{6}$$

and $\mathbf{x} = [x_1, x_2, x_3, x_4]$, in which x_i be the probability that the component is at state i, $i \in \{1, 2, 3, 4\}$.

The transition matrix in the above model is now derived. It is typically assumed that the sojourn time in a state is the exponential distribution [9]. Denote λ_{ij} as the degradation rate

FIGURE 6 Markov chain degradation prediction model.



from state i to state j, with $i \neq j$. The following equation can be obtained:

$$\frac{dx_i(t)}{dt} = -x_i(t)\sum_{j=i+1}^{4}\lambda_{ij} + \sum_{j=1}^{i-1} x_j(t)\lambda_{ji} \tag{7}$$

In (7), the term $x_i(t)\sum_{j=i+1}^{4}\lambda_{ij}$ is the intensity of transitioning from state i to the other states and the term $\sum_{j=1}^{i-1} x_j(t)\lambda_{ji}$ is the intensity of transitioning to state i from the other states. Solve (7) and discretize the solutions with sampling time [8]

$$\pi_{11} = e^{-(\lambda_{14}+\lambda_{13}+\lambda_{12})\Delta t} \tag{8a}$$

$$\pi_{12} = \frac{\lambda_{12}}{\lambda_{14}+\lambda_{13}+\lambda_{12}}\left(1-e^{-(\lambda_{14}+\lambda_{13}+\lambda_{12})\Delta t}\right) \tag{8b}$$

$$\pi_{13} = \frac{\lambda_{13}}{\lambda_{14}+\lambda_{13}+\lambda_{12}}\left(1-e^{-(\lambda_{14}+\lambda_{13}+\lambda_{12})\Delta t}\right) \tag{8c}$$

$$\pi_{14} = \frac{\lambda_{14}}{\lambda_{14}+\lambda_{13}+\lambda_{12}}\left(1-e^{-(\lambda_{14}+\lambda_{13}+\lambda_{12})\Delta t}\right) \tag{8d}$$

$$\pi_{21} = 0 \tag{8e}$$

$$\pi_{22} = e^{-(\lambda_{23}+\lambda_{24})\Delta t} \tag{8f}$$

$$\pi_{23} = \frac{\lambda_{23}}{\lambda_{23}+\lambda_{24}}\left(1-e^{-(\lambda_{23}+\lambda_{24})\Delta t}\right) \tag{8g}$$

$$\pi_{24} = \frac{\lambda_{24}}{\lambda_{23}+\lambda_{24}}\left(1-e^{-(\lambda_{23}+\lambda_{24})\Delta t}\right) \tag{8h}$$

$$\pi_{31} = 0 \tag{8i}$$

$$\pi_{32} = 0 \tag{8j}$$

$$\pi_{33} = e^{-\lambda_{34}\Delta t} \tag{8k}$$

$$\pi_{34} = 1-e^{-\lambda_{34}\Delta t} \tag{8l}$$

$$\pi_{41} = 0 \tag{8m}$$

$$\pi_{42} = 0 \tag{8n}$$

$$\pi_{43} = 0 \tag{8o}$$

$$\pi_{44} = 1 \tag{8p}$$

In this work, it is assumed that a component has a constant degradation rate when its load is less than or equal to P^{norm}, but the degradation rate exponentially increases when its load exceeds P^{norm}. This assumption is because the operating temperature starts to increase exponentially when increasing load from this point that it leads the degradation rate exponentially increases. It is noted that the control architecture contains an EM. Therefore, P is controlled to be less than its maximum capacity P as it is one of the optimization's constraints. Denote λ_{ij} the degradation rate when the component works in the region $P < P^{norm}$ and $\overline{\lambda_{ij}}$ when the component works at the maximum capacity $\overline{P}$. The degradation rate when the component works between P^{norm} and $\overline{P}$ is

$$\lambda_{ij} = \eta e^{\zeta P} \tag{9}$$

where

$$\zeta = \frac{\ln\left(\lambda_{ij}/\overline{\lambda_{ij}}\right)}{P^{norm} - \overline{P}} \tag{10a}$$

$$\eta = \frac{\lambda_{ij}}{e^{\zeta P^{norm}}}. \tag{10b}$$

A Prognostic Based Control Strategy

In the previous section, a degradation prediction methodology is proposed. In this section, a mechanism for the DF layer to interact with EM is introduced. The underlying idea is that based on the degradation results, an additional cost that takes into account components' degradation is added to the EM's objective cost. To this end, a quantity to measure the degradation components' capacity is introduced. Let $\mathbb{P}_s(t_k)$ be the maximum capacity expectation at time t_k of component s resulting from the prediction. It can be mathematically stated as

$$\mathbb{P}_s(t_k) = \sum_{i=1}^{4} x_i(t_k)\overline{P_i} \tag{11}$$

It is desired to measure how $\mathbb{P}_s(t_k)$ degrades over time. Suppose the degradation of the components is predicted from time t_0 to time t_K. The following metric is introduced to measure the capacity degradation from time t_0 to t_K of component s:

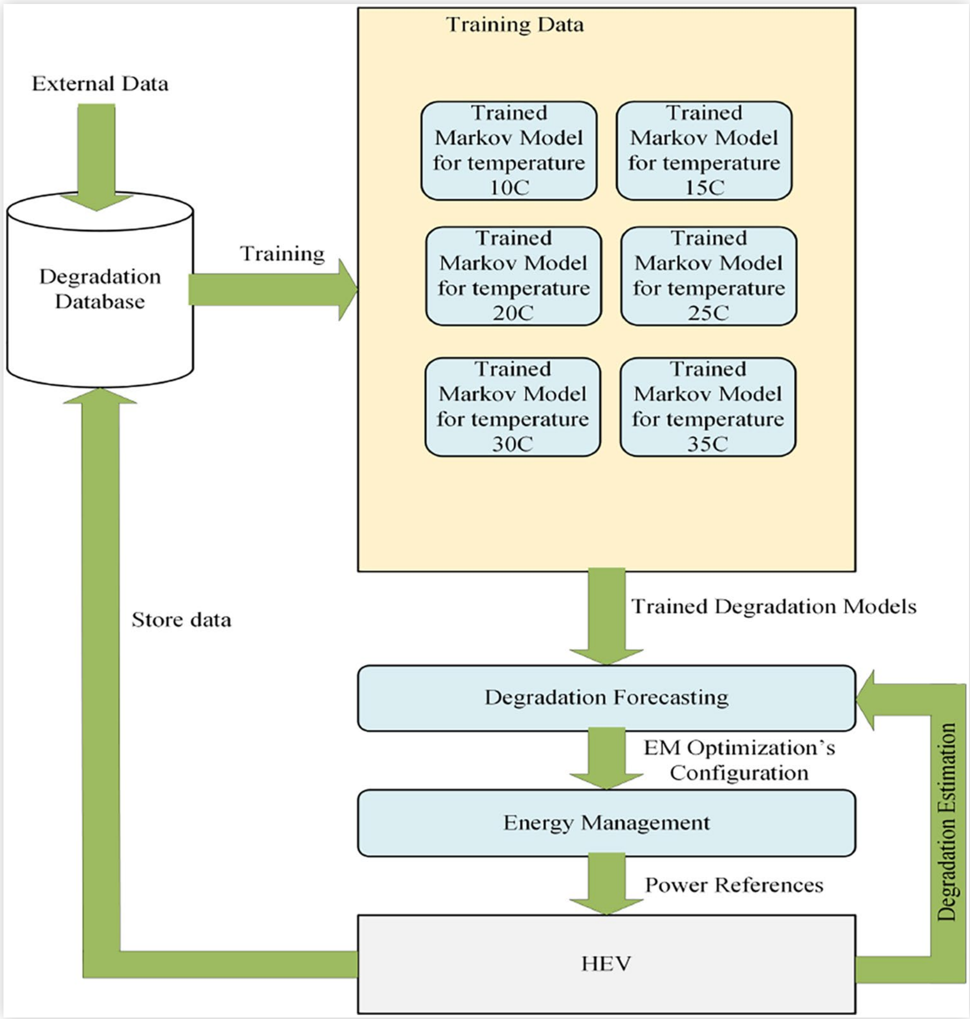
$$\Delta_s(t_K) = \mathbb{P}_s(t_0) - \mathbb{P}_s(t_K) \tag{12}$$

Suppose ρ_s is the initial cost of each capacity unit of component s. The following is added to the EM's objective cost to penalize the degradation cost.

$$f_s^d(P_s) = \rho_s \Delta_s P_s \tag{13}$$

Figure 7 illustrates the prognostic based control strategy.

FIGURE 7 Integrating degradation forecasting into control and management system for HEVs.



Numerical Simulations

In this work, the proposed scheme is validated on an HEV with powertrain illustrated in Figure 1. The capacity of HEV's ICE can generate up to 180 kW to provide the DC bus. The battery's capacity is 73 kWh. The propulsion load is typically the highest compared to the other loads when operating vehicles. In this paper, a few samples of propulsion loads are used and plotted in Figure 8. The minimum SoC is 40% and the maximum SoC is 90%.

The prediction model requires trained Markov models, which are transition matrices. For battery degradation, the Short-Term Cycling Performance Dataset dataset from Sandia National Laboratories to obtain the trained models. For the degradation of ICE, notional data is created from the Wiener process.

As of 2021, the average cost for each kWh $140 [10]. Additionally, assume the cost of the ICE is $7000. In addition, the ICE has the following efficiency curve

$$f(x) = 0.00052x^2 + 0.0152x + 0.65 \tag{14}$$

The degradation forecasting predicts the degradation of the battery and the ICE at 25°C after running 100 drive cycles in Figure 8 b). Numerical results are shown in Figure 9. As can be seen, the strategy reduces the degradation costs of HEV's components which are the battery and the ICE, by $11.94. However, the fuel cost increases $6.879. Overall, the strategy reduces $5.066 after 100 drive cycles. In addition, the strategy abates the degradation of the battery, as can been seen in Figure 9 b).

Conclusion and Future Work

In this paper, a prognostic-based control strategy for HEVs is proposed. Degradation models for HEV's components are constructed to predict their degradation paths. Based on predicted results, the HEV is controlled by adjusting EM' optimization configuration. A numerical simulation is shown to demonstrate the effectiveness of the proposed strategy.

FIGURE 8 Samples of propulsion loads.

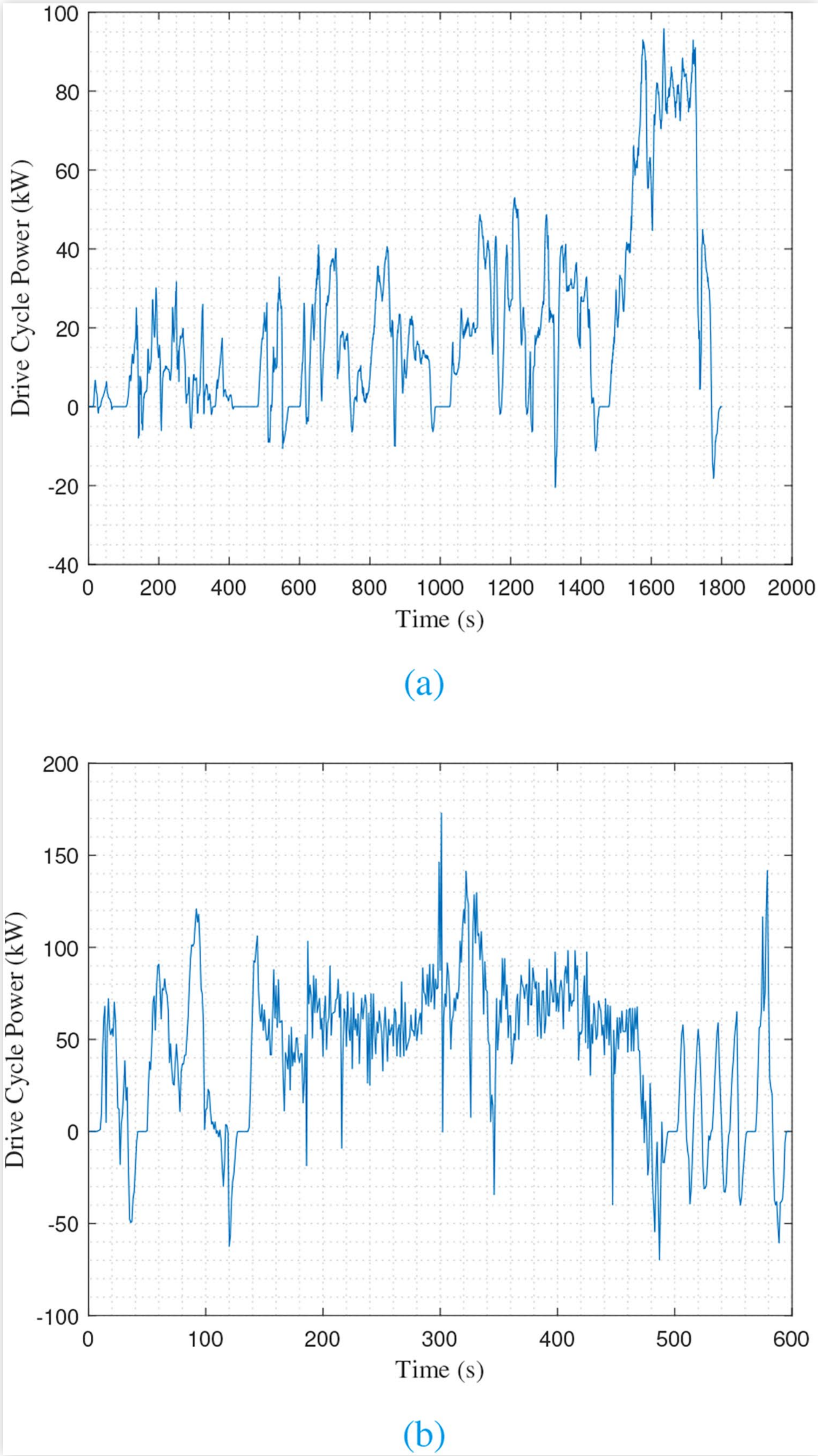
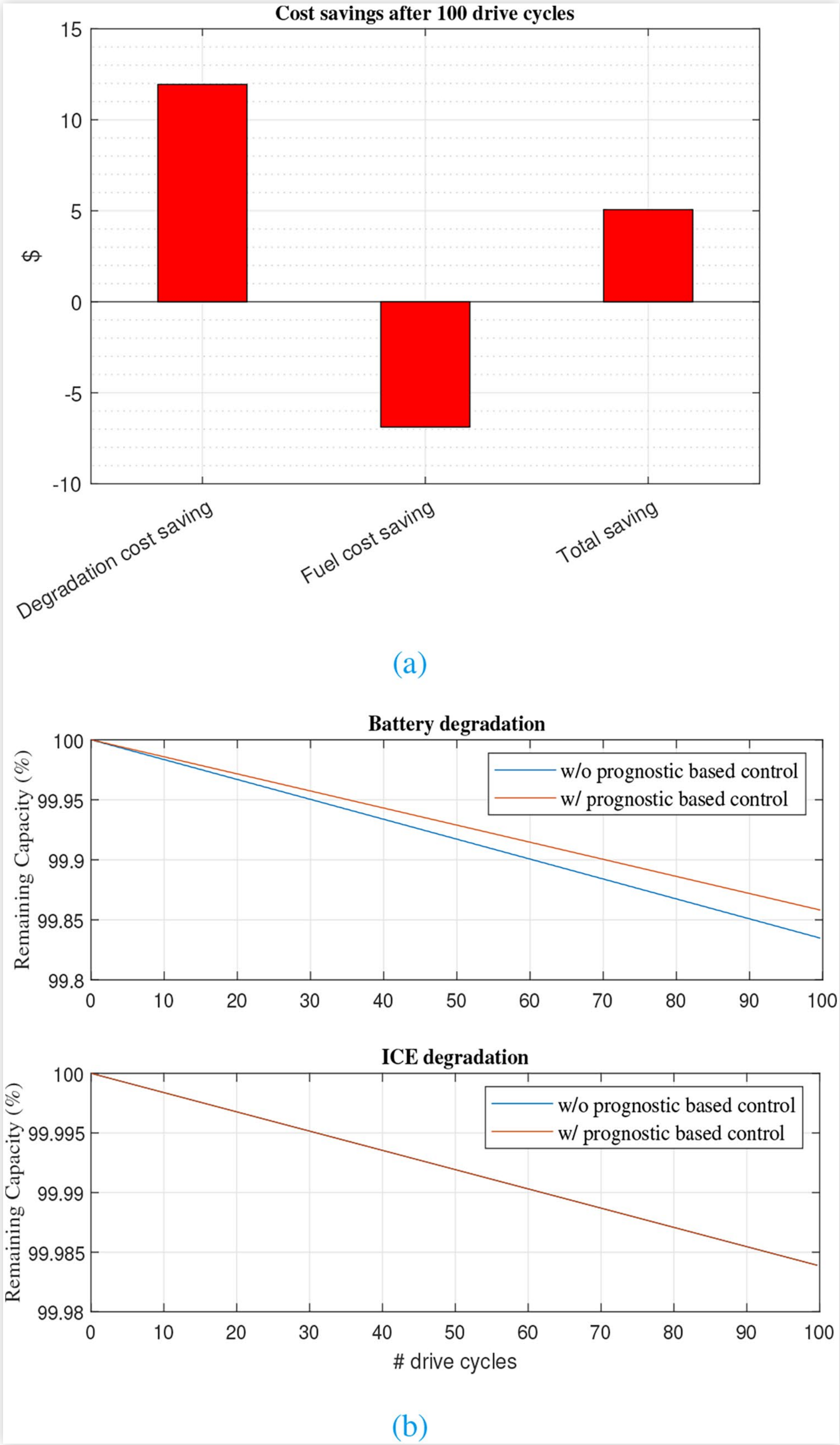


FIGURE 9 Simulation results: a) Cost savings by the proposed prognostic based strategy b) Battery degradation abatement.



Overall, the total cost of fuel consumption and components' degradation is reduced by the control strategy.

Acknowledgments

This work was supported by the Simulation Based Reliability and Safety Program for modeling and simulation of military ground vehicle systems, under the technical services contract No. W56HZV-17-C-0095 with the U.S. Army DEVCOM Ground Vehicle Systems Center (GVSC). This document was approved for public release; distribution unlimited (OPSEC 5878).

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ISSN 0148-7191