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Real-time Energy Management and Sensitivity Study for Hybrid Electric Vehicles

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Abstract— **This paper presents a real-time energy management algorithm for hybrid electrical vehicles (HEV). The proposed approach features a practical structure and manageable computation complexity for real-time implementation. It adopts a Model Predictive Control framework and utilizes the information attainable from Intelligent Transportation Systems (ITS) to establish a prediction based real-time controller structure. Simulations have been conducted with a Matlab/Simulink based vehicle model to assess the optimality of the algorithm, in comparison with existing control approaches.**

For real-time HEV control algorithms, ITS based driving prediction is an essential component. It is important to investigate the impact of the accuracy of ITS information on HEV energy consumption. In this work, we study the the effect of noises and errors in the velocity profile prediction under different control approaches. The sensitivity of the HEV energy use is investigated based on real driving data. The results provide better understanding of the need in driving profile prediction in real-time HEV control.

I. INTRODUCTION

Hybrid electric vehicles (HEV) have great potential in energy efficiency improvement and emission reduction, thanks to the additional electrical energy source. To fully exploit the potential, energy management control needs to be designed to determine the optimal power split ratio between the engine and the electric motor. The control objective is to satisfy the power demand and to optimize fuel economy and emission.

There has been extensive research in this field during the last decade. Various rule based controls have been presented for real-time implementation ([9], [12]). Also, analytical optimization algorithms based on Dynamical Programming (DP) ([1], [4]) and Equivalent Consumption Minimization Strategy (ECMS) ([7], [8]) are developed. For a detailed summary, the readers are referred to [10]. ECMS is based on Pontryagin's Minimum Principle, and features an equivalence factor which characterizes the equivalent fuel for the electrical energy consumption. It has been proved that with proper choice of the equivalence factor, ECMS is able to achieve the optimum performance ([8]). However, the calculation in DP and optimal ECMS requires full knowledge of the velocity and power demand profile of the driving cycle. Therefore, they are not suitable for practical implementations. There have been variations of ECMS for real-time implementation. For example, Adaptive ECMS (A-ECMS, [5], [6]) and Telemetry ECMS ([11]) algorithms adjusts the equivalence factor based on past driving data and future prediction . Also, pattern recognition based approaches define a number of driving patterns and pre-calculate the optimal equivalence factors for each of them. They identify the pattern during the actual driving and apply appropriate value of the equivalence factor ([2]).

To achieve effective real-time implementation, the HEV energy management controller typically requires information of future velocity and power load over an appropriate time horizon. [3] demonstrated that for an urban route with varying topography, predictive control could significantly improve fuel economy. Intelligent Transportation Systems, in particular, on board vehicle navigation systems, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications could provide information feed necessary to build the driving prediction. The existing works in real-time HEV control usually assume the information is accurate for the prediction needs. However, noises, errors and delays are inevitable in ITS systems, due to limitation of sensing and communication equipments. Therefore, it is important to study the sensitivity of different control strategies with respect to different types of errors and noises in ITS information. The results can be utilized to aid HEV information processing and energy management system design. For example, based on the impact of different factors, the designers can tailor the communication and computing power for different types of information, as well as to optimize control decisions.

The first part of this paper presents an Efficiency based Model Predictive Control (OE-MPC) approach that utilizes ITS information to minimize fuel consumption. At each step, it aims to optimize engine efficiency for a specified control horizon. The proposed approach has a practical structure and manageable computation complexity to permit real-time implementation. The approach is also extendable to Plug-in HEVs.

In the second part, we study the the effect of noises and errors in the velocity profile prediction under different real-time control approaches, including OE-MPC and A-ECMS control. Real driving data have been utilized for sensitivity study. The results provide better understanding of the need in driving profile prediction in real-time HEV control.

The paper is organized as follows. Section 2 presents the problem formulation of HEV energy management. Section 3 elaborates the proposed MPC based real-time control strategy, and illustrates the simulation results on different driving cycles. Section 4 focuses on sensitivity study with

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respect to noise in velocity prediction. Section 5 provides the conclusion.

II. Problem Formulation

The objective of HEV energy management is to minimize fuel consumption and emission, while ensuring battery charge sustaining. The amount of emission is typically closely related to the fuel use. Therefore, we consider the objective function as the overall fuel consumption of a trip:

$$J = \int_{t_0}^{t_f} \dot{m}_{ff} d\tau$$

subject to the constraint on battery state of charge (SOC):

$$SOC(t_f) = SOC(t_0)$$

The optimal power-split ratio between Electric Motor (EM) and Internal Combustion Engine (ICE) is to be determined to minimize J. The optimization is also subject to the following physical constraints at all times:

$$\begin{array}{l} SOC_{\min} < SOC < SOC_{\max} \\ T_{em} + T_{ice} = T_{wh} \\ T_{em,\min} \leq T_{em} \leq T_{em,\max} \\ T_{ice,\min} \leq T_{ice} \leq T_{ice,\max} \end{array} \quad (1)$$

where $SOC_{\min}$ and $SOC_{\max}$ are lower and upper bounds of battery state of charge. The control variables T_{em} and T_{ice} are the torques to be allocated from EM and ICE respectively, and T_{wh} is the torque demand of the vehicle. The values $T_{em,\min}$ and $T_{em,\max}$ are lower and upper bounds of EM torque, and they vary with the motor angular speed. Similarly, $T_{ice,\min}$ and $T_{ice,\max}$ are lower and upper bounds of ICE torque, depending on the engine speed.

The vehicle model considered here is an HEV of parallel architecture, where the EM and ICE drive the rear axle and the front axle respectively. A Matlab/Simulink based vehicle simulator is utilized here. To simplify control design and simulation, a quasi-static forward model of the powertrain is adopted in the simulator. The torque generation, battery charging and discharging efficiency, the efficiency and energy use characteristics of the engine and motor are specified by static maps. The efficiencies of the gearbox, transmission and battery are defined as constants. This way, the dynamics of the overall system is simplified to a first-order system with the state variable being the battery state of charge:

$$\dot{SOC} = \begin{cases} \frac{\eta_{batt}(i)}{C_{nom}} i, & i > 0 \\ \frac{1}{\eta_{batt}(i) C_{nom}} i, & i < 0 \end{cases}$$

where η_{batt} is battery charging or discharging efficiency, C_{nom} is the battery nominal capacity, and i is the battery current. The battery is charged with $i > 0$, while discharged with $i < 0$.

III. Model Predictive Control For Optimal Engine Efficiency

Fig. 1 illustrates the controller structure. The algorithm defines two threshold levels η_c and η_d regarding engine efficiency η and optimizes their values in real time. Denote

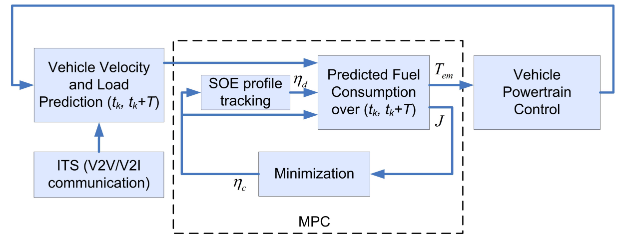

Fig. 1. The real-time energy management controller structure.

TABLE I

OE-MPC: optimization process of η_c and η_d at time instant t.

for η_c = $\eta_{c,\min}$:$\Delta\eta_c$:$\eta_{c,\max}$
  for η_d = $\eta_{d,\min}$:$\Delta\eta_d$:$\eta_{d,\max}$
    calculate projected $SOC(t+T)$ based on driving profile prediction and η_c;
    calculate projected fuel consumption over $(t, t+T)$;
  end
  record the value of η_d that minimizes $|SOC(t+T) - SOC_r(t+T)|$;
end
find the combination of $(\eta_c, \eta_d(\eta_c))$ that minimizes the fuel consumption over $(t, t+T)$;

the prediction horizon as T. At each time instant t, the optimization objective is

$$J(t) = \int_{t}^{t+T} \dot{m}_{ff} d\tau$$

subject to the constraints in (1). There could be a higher level planning to determine an SOC reference profile SOC_r over a longer time horizon. In that case, the terminal constraint of the MPC is given by

$$|SOC(t+T) - SOC_r(t+T)| < \epsilon$$

where $\epsilon > 0$ is a small constant. The simplest reference SOC is $SOC_r(t) = SOC(t_0)$ for all $t \geq t_0$. In each step, the values of the threshold levels η_c and η_d are optimized to determine the power split ratio over $(t, t+T)$ that ensures tracking of a reference SOC profile and minimization of $J(t)$.

The implementation of the optimization process is illustrated in Tab. I. For a given set of (η_c, η_d), the power split ratio calculation is rule-based. For each time instant, when the optimal engine efficiency corresponding to the engine speed is greater than η_c, and the torque demand is less than the optimal engine torque, the battery is set to store the excess power such that the engine operates at the maximum efficiency point. On the other hand, when the predicted engine efficiency corresponding to the engine speed and torque demand is lower than η_d, then the battery may need to supply power. In particular, if the torque demand is within the ability of the electric motor, the battery is to supply the required torque. If the torque demand exceeds the engine optimal torque, the battery supplies an appropriate amount of torque such that the engine efficiency is maximized. Also, the battery is charged when there is regenerative braking.

The proposed approach is verified with the Matlab/Simulink based HEV simulator. The specification of the

TABLE II

A-ECMS: OPTIMIZATION OF s AT TIME INSTANT t.

```
for s = s_min:Δs:s_max
      find the optimal power split ratio to minimize the projected
      fuel consumption over (t, t + T)
      calculate projected SOC(t + T) based on driving profile
      prediction and s;
   end
   record the value of s that minimizes
   |SOC(t + T) − SOC_r(t + T)|;
end
```

TABLE III

VEHICLE SPECIFICATIONS

Vehicle weight	1500 kg
Engine	1.9L, 103 kW
Fuel	20%Biodiesel (B20)
Electric Machine	67 kW, Induction motor
Battery size	2.32 kWh

vehicle is given in Tab. III. The driving cycle inputs are the Urban Dynamometer Driving Schedule (UDDS) with scale factors from 1.0 to 1.3 to simulate the effect of normal and aggressive driving. Tab. IV summarizes the simulation results in terms of equivalent fuel economy in miles per gallon (MPG), in comparison with fuel only driving, ECMS control, and Adaptive ECMS control. In the simulation, the initial SOC is 0.7 and the lookahead horizon is $T = 60$ sec. The A-ECMS implemented here is based on the structure in [5]. As shown in Tab. II, at each time instant, it searches for an equivalence factor s that minimizes $|SOC(t+T)-SOC_r(t+T)|$. The equivalent fuel economy calculation considers the electrical energy use:

$$Fuel_{el} = \begin{cases} \frac{1}{\eta_e \eta_t} \frac{E_{batt}}{LHV_{B20}} & E_{batt} > 0 \\ \frac{\eta_t}{\eta_e} \frac{E_{batt}}{LHV_{B20}} & E_{batt} < 0 \end{cases}$$

$$MPG_{eq} = \frac{D}{Fuel_{B20} + Fuel_{el}}$$

where E_{batt} denotes the battery energy use, $Fuel_{el}$ represents its equivalent fuel amount in gallons, $\eta_e = 0.3$ is the average engine efficiency, $\eta_t = 0.77$ represents the transmission and battery efficiency, $LHV_{B20} = 34.32$ kWh/gallon is the low heat value of B20, MPG_{eq} is the energy based equivalent MPG, D is the total mileage of the trip, and $Fuel_{B20}$ denotes the amount of B20 consumed.

As an example, Fig. 2 illustrates the simulation result of optimal engine efficiency based MPC (OE-MPC) on UDDS. As shown in the figure, the final SOC is also 0.7, satisfying the charge sustaining requirement. The resulted MPG is 52.2, which is slightly smaller than that of 53.1 from the ECMS approach. However, the latter requires accurate prior knowledge of the full trip and a trial-and-error search for the optimal equivalence factor. Fig. 3 illustrates the SOC profiles on UDDS with 1.3 times faster driving speed.

IV. SENSITIVITY STUDY

Due to the inevitable error and noise in the prediction of future velocity and power load profile, investigation of the sensitivity of HEV energy use on prediction error is necessary. We study the sensitivity issue of the proposed approach with respect to noise in the velocity prediction, in comparison to the A-ECMS approach which is also real-time implementable.

Two different sets of study have been conducted, based on experimentally measured driving cycles. The velocity profiles have been recorded along an urban route from the Center for Automotive Research (CAR), the Ohio State University to the university main campus. The route is about 2 miles in distance, and consists of urban roads with a highest speed limit of 35mph. Fig. 4 shows an overview of the route. In the first case, different sections of UDDS cycle are used as velocity predictions supplied to the HEV controller, while the simulator is run on an actual driving cycle that is different from UDDS. The second part of the study uses one of the actual cycles as the velocity prediction for the simulation of a total of twelve different driving cycles along the same route.

A. UDDS as prediction

A representative measured driving cycle (Fig. 5) from CAR to OSU main campus is simulated using different sections of UDDS as velocity predictions. As shown in Fig. 6, four different sections of UDDS are adopted for the test. The total travel distance of each section is very close to that of the CAR-OSU driving cycle. The difference between the UDDS sections and the CAR-OSU cycle results in velocity prediction error for the control of the HEV. The simulation results are illustrated in Fig. 7, where the x-axis

TABLE IV

FUEL ECONOMY OF DIFFERENT CONTROL APPROACHES.

UDDS×	1	1.1	1.2	1.3
Fuel only	40.2	37.7	35.8	34.3
ECMS	53.1	49.3	46.1	43.4
OE-MPC	52.2	48.7	45.9	44.3
A-ECMS	52.5	49.0	45.8	43.1

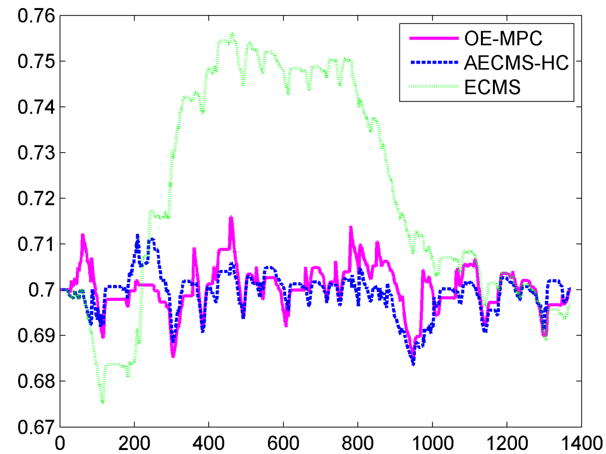

Fig. 2. The optimal SOC profiles for UDDS cycle.

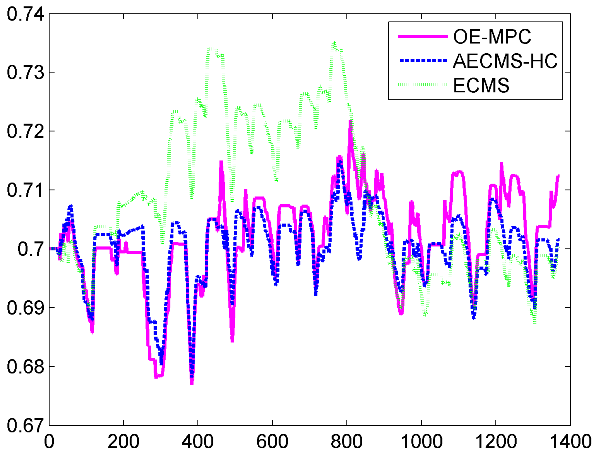

Fig. 3. The optimal SOC profiles for UDDS×1.3 cycle.

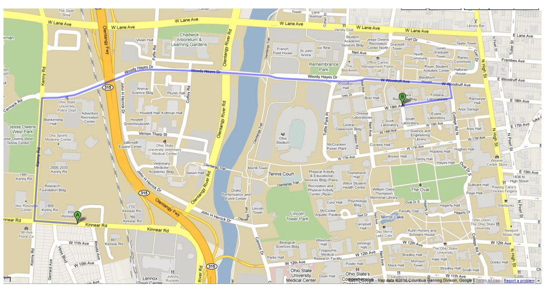

Fig. 4. The urban route for the test driving cycles (google map).

represents number of simulations. In particular, simulation No. 1 is the nominal case where the controllers are given the correct prediction of the actual driving cycle. Simulation No. 2-5 represent the results with UDDS sections I-IV as predictions respectively. The simulation shows up to eight percent deviation in equivalent MPG from the nomial case. In particular, the OE-MPC approach exhibits larger deviation in the final SOC under prediction error. The underlying mechanism for the different effects of inaccurate prediction on different algorithms is under further study.

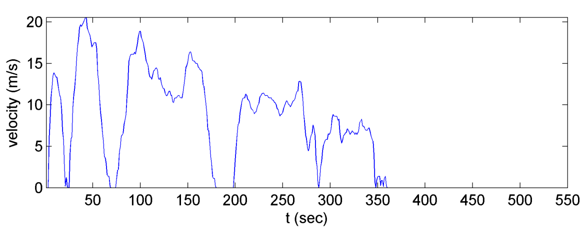

Fig. 5. A velocity profile from CAR to OSU main campus.

B. Real driving data as prediction

The second set of study is based on 12 driving cycles along the same route from CAR to OSU main campus. For the sensitivity study, we use Cycle No. 1 as the velocity prediction and feed it into the real-time controllers. Then the

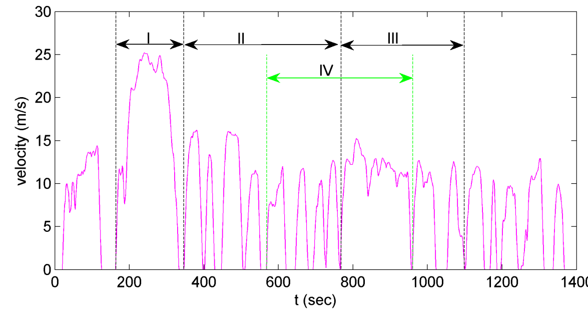

Fig. 6. Sections of UDDS as velocity predictions for the CAR-OSU trip.

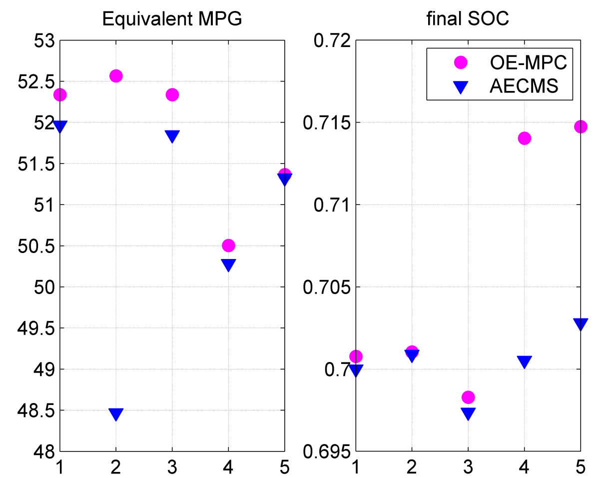

Fig. 7. The results with velocity prediction from UDDS sections.

HEV simulator is run on all 12 cycles. As a result, velocity prediction error is introduced as the difference between Cycle No. 1 and the actual driving cycle the simulator is running on. Fig. 8 illustrates the the prediction noise for Cycle No. 2. The simulation results are shown in Fig. 9. While OE-MPC and A-ECMS respond differently to the prediction noise, both control approaches regulate the SOC level well despite the presence of the noise. The final SOC of all runs are close to the initial value of 0.7.

For comparison, simulations with no prediction noise are conducted for all driving cycles, where the controller has access to the actual driving cycle. Fig. 10 and Fig. 11 compare the results for OE-MPC and A-ECMS respectively. The maximum deviation of the equivalent MPG from the prediction noise for both approaches is about four percent. This result points to a possibility that HEV control might be able to use a representative driving profile in place of real-time prediction for typical driving routes and yield close-to-optimal fuel economy. Further studies covering more diverse driving conditions such as highway and urban routes, and driving under different weather and temperature are necessary to reach a conclusive result. Then we can weigh the benefit of accurate ITS based trip prediction against the equipments and development cost to determine a cost effective HEV control design.

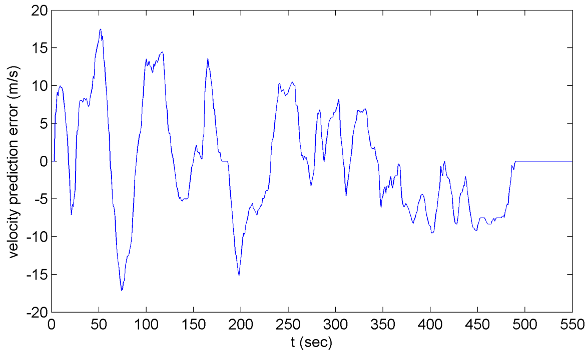

Fig. 8. The prediction error for Driving Cycle No. 2.

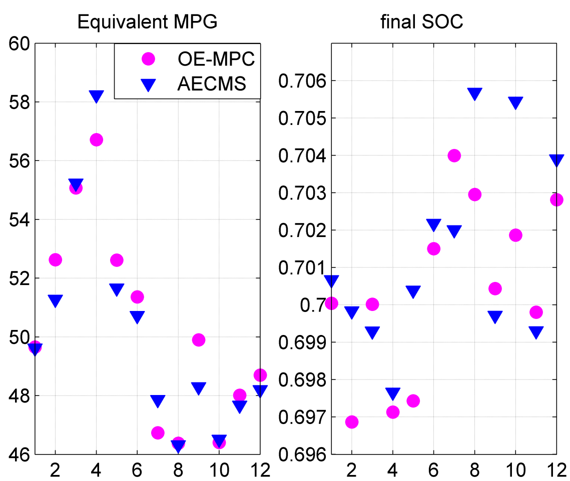

Fig. 9. Sensitivity test with respect to prediction error.

V. CONCLUSION

The proposed approach has a practical structure and limited computation complexity to permit real-time implementation. Simulation tests have been conducted on a Matlab/Simulink based vehicle simulator. Results show that the achieved fuel economy has significant improvement from fuel only driving, and is comparable to that of ECMS and A-ECMS when the velocity and load prediction is noise free.

Also, the effect of noises and errors in the velocity profile prediction is studied under different control approaches. Sensitivity study has been conducted with real driving data. The results vary among different controllers. With proper choice of velocity prediction data for the controller, only small deviation in the final SOC and fuel economy are introduced. The results provide better understanding of the need in driving profile prediction in real-time HEV control.

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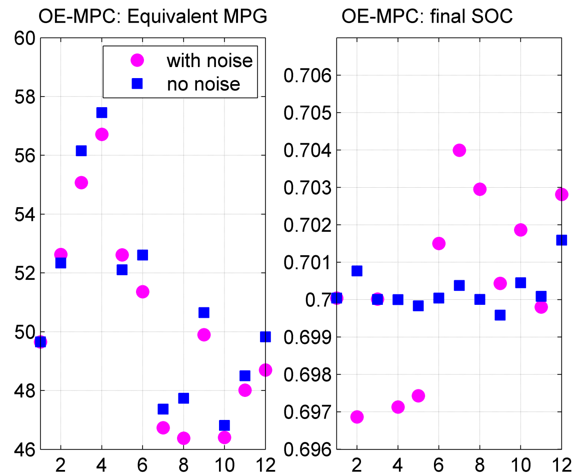

Fig. 10. The effect of prediction error with OE-MPC.

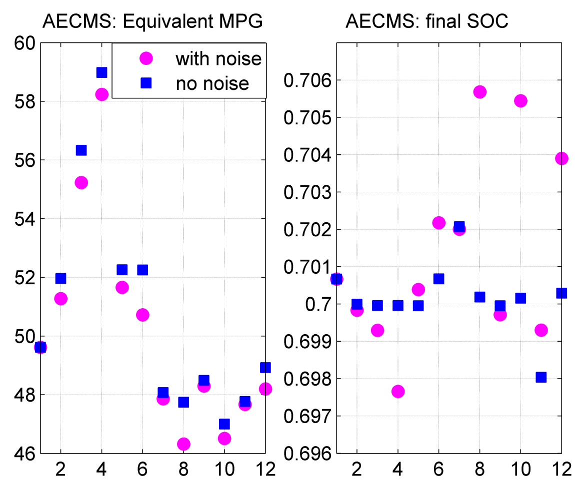

Fig. 11. The effect of prediction error with A-ECMS.

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