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Real-Time Markov Chain Driver Model for Tracked Vehicles

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Abstract: The design of an energy management strategy for a hybrid electric vehicle typically requires an estimate of requested power from the driver. If the driving cycle is not known a priori, stochastic method such as a Markov chain driver model (MCDM) must be employed. For tracked vehicles, steering power, which is related to the vehicle angular velocity, is a significant component of the driver demand. In this paper, a three-dimensional MCDM incorporating angular velocity for a tracked vehicle is proposed. Based on the nearest-neighborhood method (NNM), an online transition probability matrix (TPM) updating algorithm is implemented for the three-dimensional MCDM. Simulation results show that the TPM is able to update online when the driving cycle is available. Moreover, the older and recent observations can be weighted appropriately by adjusting a forgetting factor.

Keywords: Markov chain driver model (MCDM), tracked vehicle, nearest-neighborhood method (NNM), transition probability matrix (TPM), online updating algorithm, energy management.

1. INTRODUCTION

With the hybrid vehicles being introduced to the market in recent years and having the potential to reduce the fuel consumption and emissions, an energy management strategy needs to be proposed to coordinate the operation of the multiple energy sources on board (Choi et al. [2014], Emadi et al. [2005]). Even though it is impossible to know exactly the future driving conditions (speed, road slope etc.), the global optimal approach solved by deterministic dynamic programming (DDP) is widely used as a benchmark for other strategies (Salmasi [2007], Malikopoulos [2014]), and to improve performance by appropriate rule extraction (Lin et al. [2003]). As an alternative, stochastic control avoids perfect assumption about the future driving by modelling the driver's behaviour as a stochastic input to the energy management controller. Due to the simplification of the mathematical expression and the easy incorporation with the optimal control, the Markov chain (Grimmet and Stirzaker [2004]) based driver model has been successfully utilized to lay the foundation for the stochastic control approaches as opposed to the deterministic ones.

A Markov process (or Markov chain) is a system that can be in one of several states and can move from one state to another state, including itself, each time step according to a transition probability matrix (TPM). The Markov property states that the future states are independent of the past states given the present state (Grimmet and Stirzaker [2004]). The verification of the Markov property can be found in some previous papers (Shi et al. [2013]). Many researches focused on the Markov chain based driver stochastic energy management strategies. Stochastic Model Predictive Control (SMPC) is promising to outperform the other real-time energy managements by the underlying assumption that the power requested from the driver is represented by a Markov model (Cairano et al. [2014]). Because of the probability distribution of the drivers' power request, the cost function can be minimized in an expected form. Considering the vehicle velocity, a two-dimensional Markov chain described the drivers' behaviour more accurately. An infinite-horizon optimization problem with the discounted future costs is solved by using the Stochastic Dynamic Programming (SDP) (Liu and Peng [2008]). A weakness of the SDP approach is that the optimization criterion discounts the future costs and assigns a penalty to the battery State of Charge (SOC) at every instant (Tate et al. [2008]). To solve this problem, a terminal state representation when the vehicles turn off is added to the two-dimensional Markov chain mentioned above. The terminal state turns to absorbing: every state transitions into it in finite time. Once in the terminal state, no costs are incurred and there is zero probability of transitioning out of it. The existence of this terminal state forms a Shortest-Path Stochastic Dynamic Programming (SP-SDP) problem, guaranteeing the expected objective cost to be finite with no discount, and only penalizing the SOC deviation from a set point when the vehicle is turned off (Tate et al. [2008]). A similar Markov chain containing the terminal state is proposed in recent years (Opila et al. [2012]), where the vehicle velocity and the acceleration constitute the state space. The above Markov chain models are all stationary, which means the model is invariant for the time and position, hence a position-dependent Markov chain with the states of the vehicle velocity and acceleration is established to assess the potential of SDP's predictive control ability in contrast to a homogeneous Markov chain with vehicle velocity and power request as the states (Johannesson et al. [2007]).

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Even though much attention has been paid to the Markov chain model application to the stochastic energy management strategy for HEVs, the research on the Markov chain driver models (MCDMs) for tracked vehicles is scarce. Significantly differing from the wheeled vehicle, the power consumption during steering is much higher than that during heading straight for tracked vehicle (Wang et al. [1983]). A stochastic driver model incorporating the heading and steering motion is high in demand. Previous research on the stochastic control for tracked vehicles neglects the steering power so that the MCDM is still a two-state Markov chain in consideration of the heading power and velocity (Zou et al. [2012a]). Moreover, the driver behaviour is also affected by the surrounding environment all the time, for instance due to the variant traffic conditions, the road types, and the driver emotional states and objectives. Therefore, the MCDM should have the flexibility to real-time update to reflect the changes of the driver behaviour. In other words, TPM can update online by utilizing the new velocity data provided by telematics systems on board (Cairano et al. [2014]), unlike the offline estimation of the TPM on the basis of observed sample data, such as standard driving cycles, or past driving records (Liu and Peng [2008]).

This paper discusses a new MCDM for tracked vehicles and a TPM online updating algorithm based on nearest-neighbourhood method (NNM) with a forgetting factor adjusting the weights between older and recent observations. A comparison measurement of TPMs called the Kullback-Leibler (KL) divergence (Rached et al. [2004]) is applied to quantize the difference between the updated time-variable TPMs.

The remainder of the paper is arranged as follows: Section 2 introduces the MCDM for tracked vehicles and formulates the TPM online updating algorithm; moreover, the KL divergence is expounded; the results are discussed in Section 3; Section 4 concludes this paper.

2. A NEW MCDM FOR TRACKED VEHICLES AND ONLINE UPDATING ALGORITHM FOR NNM

2.1 MCDM for Tracked Vehicles

An essential task in constructing an MCDM is to express the power demand in a form that is computationally simple, but with adequate precision. The general force diagram of a tracked vehicle is shown in Fig. 1.The demanded power to propel the vehicle, P_{dem}, is calculated as the combination of heading power and steering power (Wong [2001])

$$P_{dem} = (F_i + F_a + F_r)v_{ave} + M\omega \tag{1}$$

where the first product is the heading power and the second is the steering power. F_i is the inertial force, F_a is the aerodynamic drag, F_r is the rolling resistance, v_{ave} is the average speed of vehicle, M is the resisting yaw moment from the ground assuming steady-state turning and ω is the rotational speed of the vehicle.

When the slippage of the tracks is not considered, the vehicular average heading speed v_{ave} is calculated as Eq. (2)

$$v_{ave} = \frac{v_1 + v_2}{2} \tag{2}$$

where v_1 and v_2 are the speeds of two tracks. The vehicular rotational speed is calculated as Eq. (3)

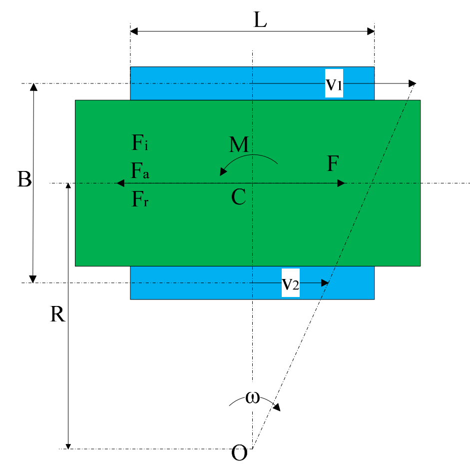

Fig. 1. Force diagram of tracked vehicles

$$\omega = \frac{v_1 - v_2}{B} \tag{3}$$

where B is the tread of the vehicle.

The value of F_i is evaluated by

$$F_i = ma \tag{4}$$

where m is curb weight and a is the acceleration. The value of F_a is calculated by

$$F_a = \frac{C_d A}{21.15} v_{ave}^2 \tag{5}$$

where A is the fronted area and C_d is the aerodynamic coefficient. The rolling resistance F_r is computed by

$$F_r = mg \cdot f \tag{6}$$

where f is the rolling resistance coefficient and g is the acceleration of the gravity. The value of M is calculated by

$$M = \frac{1}{4} u_t mgL \tag{7}$$

where L is the contacting length of tracks and the coefficient of the lateral resistance u_t is computed based on empirical results (Wang et al. [1983])

$$u_t = u_{\max} / (0.925 + 0.15R / B) \tag{8}$$