Applied Energy 182 (2016) 105–114

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Model predictive control-based energy management strategy for a series hybrid electric tracked vehicle

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HIGHLIGHTS

- The configuration and modeling process for HETB are presented.
- A model predictive control-based energy management strategy for HETB is proposed.
- A comparative study between the MPC, rule-based, and DP is conducted.
- Results show MPC performs closely to DP and better than rule-based in fuel economy.
- The robustness of the MPC-based energy management strategy is also verified.

ARTICLE INFO

Article history:
Received 21 June 2016
Received in revised form 11 August 2016
Accepted 15 August 2016
Available online 25 August 2016

Keywords:
Series hybrid electric tracked bulldozer
Energy management strategy
Model predictive control
Rule-based
Dynamic programming
Robustness

ABSTRACT

The series hybrid electric tracked bulldozer (HETB)'s fuel economy heavily depends on its energy management strategy. This paper presents a model predictive controller (MPC) to solve the energy management problem in an HETB for the first time. A real typical working condition of the HETB is utilized to develop the MPC. The results are compared to two other strategies: a rule-based strategy and a dynamic programming (DP) based one. The latter is a global optimization approach used as a benchmark. The effect of the MPC's parameters (*e.g.* length of prediction horizon) is also studied. The comparison results demonstrate that the proposed approach has approximately a 6% improvement in fuel economy over the rule-based one, and it can achieve over 98% of the fuel optimality of DP in typical working conditions. To show the advantage of the proposed MPC and its robustness under large disturbances, 40% white noise has been added to the typical working condition. Simulation results show that an 8% improvement in fuel economy is obtained by the proposed approach compared to the rule-based one.

1. Introduction

Construction vehicles, such as bulldozers, play a significant role in modern society. The increasing reliance on construction vehicles brings serious adverse impacts such as unsustainable energy use and poor air quality. Recently, hybrid electric construction vehicles have appeared. Caterpillar produced the first hybrid electric tracked bulldozer, D7E, in March 2008. Compared to traditional models, D7E's CO and NO_x emissions were reduced by approximately 10 and 20%, respectively. The D7E model can improve fuel economy by 25%. In this paper, a new HETB composed of an engine-generator, two drive motors, and an ultracapacitor pack is put forward. The powertrain topology of the HETB is shown in Fig. 1. This HETB uses an integrated controller to manipulate two separate motors on the two sides. The added electric motors and ultracapacitors provide more flexibility to meet power demands and achieve minimal fuel consumption [1]. The performance or fuel economy of the HETB is heavily dependent on its energy management strategy, which uses a supervisory controller that can coordinate the energy flow between different energy sources and enhance the overall efficiency of the powertrain [2].

Recently, numerous energy management strategies have been reported and applied to hybrid electric vehicles (HEVs) [3–6], and these strategies can be divided into four classes [7]. The first type refers to the numerical optimization method, where the entire or partial drive cycle is required and the global or local optima is found numerically; this type includes the DP [8–10], MPC [11,12] and stochastic DP [13]. DP provides a globally optimal solution and is mainly employed as a good benchmark for optimality

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http://dx.doi.org/10.1016/j.apenergy.2016.08.085
0306-2619/

Nomenclature

F_E	external travel resistance, N
F_T	operating resistance, N
F_c	compaction resistance, N
F_b	bulldozing resistance, N
G	vehicle's weight, N
b	width of the track, m
L′	length of the track, m
c	soil cohesion coefficient, kPa
Ψ	soil internal friction angle, °
k	soil deformation modulus, KN/m^{n+2}
n	soil deformation index
Z	track's amount of sinkage, m
γ	soil unit weight, N/m^3
N_γ, N_c	soil Terzaghi coefficients of the bearing capacity
F_1	cutting force, N
F_2	pushing force of the mound ahead of the blade, N
F_3	friction resistance between the blade and ground, N
F_4	component of the frictional resistance in horizontal direction when the soil rises along the blade, N
B_1	bulldozer plate width, m
H	bulldozer plate height, m
k_b	cutting force per unit area, MPa
G_t	soil weight in front of the bulldozing plate, N
h_p	bulldozer average cutting depth, m
μ_1	friction coefficient among soil particles
μ_2	friction coefficient between the soil and bulldozing plate
Vol	the soil volume in front of the bulldozing plate, m
θ	slope, °
k_s	soil loose degree coefficient
k_y	cutting force per unit area when the plate is penetrated into the soil, MPa
k_m	soil fullness degree coefficient
α_0	natural slope angle of the soil, °
X	bulldozing plate worn length contacting the ground, m
δ	cutting angle of the bulldozing plate, °
N_e	speed of engine, rpm
P_e	engine output power, kW
T_e	engine torque, N
n_m	motor speed, rpm
T_m	motor output torque, N
P_{uc}	output power from the ultracapacitor, kW
P_g	generator output power, kW
η_m	motor efficiency
C	equivalent capacitance of ultracapacitor, F
SOC	state of charge of ultracapacitor
SOE	state of energy of ultracapacitor

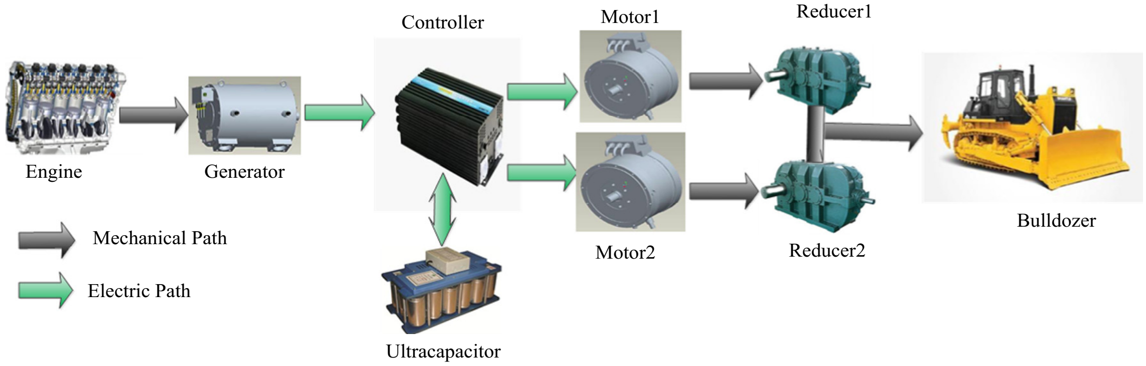

Fig. 1. Configuration of the HETB.

comparison [14]. In the literature [6], authors firstly propose a novel correctional DP-based energy management strategy that takes characteristics of the drive cycle and hybrid powertrain into consideration to realize the significant improvement of fuel economy and at the same time to ensure drivability during slope conditions. The second class represents the analytical optimization method including Pontryagin's minimum principle and the Hamilton-Jacobi-Bellman equation [15]. The third type is the equivalent consumption minimization strategy (ECMS) [16], which decides the optimal power split ratio between different energy sources at each step [17,18]. Furthermore, the ECMS method does not require future driving information as it solves an instantaneous optimization problem. Given a proper equivalent factor, ECMS could potentially achieve sub-optimal fuel economy [19]. Nevertheless, it is nontrivial to tune the equivalent factor, and ECMS cannot produce globally optimal performances. ECMS is able to adjust the factor via an adaptive ECMS as long as the future driving information can be identified online to achieve better fuel economy [20,21]. The fourth category employs fuzzy logic, heuristic rules, and neural networks for energy management strategy design [22,23].

The MPC is prevalent and widely employed in HEVs nowadays as an effective approach to deal with multivariable constrained control problems, and this strategy can be treated as a tradeoff between DP and ECMS. Currently, different kinds of MPCs are widely utilized because of their ability to deal with multivariable constrained problems and their potential for the real-time application as a receding horizon control strategy. Meanwhile, the MPC has also shown its potential for application in HEVs [24–28]. An MPC solves an energy management problem at every time instant by quadratic programming [29], nonlinear programming [30], Pontryagin's minimum principle [31], and stochastic DP [32]. In [33], a stochastic MPC was designed for a series HEV, where a Markov chain was used to model the future power demand. Its performance was compared to that of a prescient MPC with a fully known power demand and a frozen-time MPC using a constant power demand in the prediction horizon to demonstrate its fuel economy in a condition similar to the ideal condition (prescient MPC). Literature [34] developed an MPC for energy management with the capability to account for the uncertainty caused by traffic, destination, and weather. A modified k-nearest neighbor regressor was utilized to generate weighted samples of the upcoming drive cycle