Applied Energy 111 (2013) 1001–1009

Contents lists available at SciVerse ScienceDirect

Applied Energy

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

Energy efficiency analysis of a series plug-in hybrid electric bus with different energy management strategies and battery sizes

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HIGHLIGHTS

- Recuperation and fuel to traction efficiencies are analyzed for a PHEV powertrain.
- Two different energy controls are compared in terms of the two efficiencies.
- Impact of battery downsizing on the two efficiencies is quantified.
- Convex modeling and optimization are used to analyze the powertrain.

ARTICLE INFO

Article history:
Received 8 February 2013
Received in revised form 15 May 2013
Accepted 29 June 2013

Keywords:
Recuperation efficiency
Fuel-to-traction efficiency
TTW analysis
Plug-in hybrid electric vehicle
Convex optimization

ABSTRACT

This paper is concerned with the tank to wheel (TTW) analysis of a series plug in hybrid electric bus operated in Gothenburg, Sweden. The bus line and the powertrain model are described. The definition and the calculation method of the recuperation and fuel to traction efficiencies are delineated for evaluating the TTW energy conversion. The two efficiencies are quantified and compared for two optimization based energy management strategies, in which convex modeling and optimization are used. The impact of downsizing the battery on the two efficiencies is also investigated.

1. Introduction

Oil supply uncertainty, growing mobility demand, and increasingly stringent regulations on pollutants and carbon footprint are expediting a paradigm shift towards sustainable transportation [1 3]. As key ingredients, hybrid electric vehicles (HEVs) are being actively developed by automotive companies worldwide to pursue higher fuel economy than conventional internal combustion engine (ICE) vehicles without inducing range anxiety [4 8]. Owing to vehicle to grid (V2G) services, plug in hybrid electric vehicles (PHEVs) potentially can take advantage of renewable energy sources to reduce reliance on fossil fuels and thus are an important solution to reducing carbon dioxide emission in the transportation sector [9,10].

In order to evaluate the total energy consumption and carbon dioxide emission of a vehicle in a broad sense, well to wheel (WTW) analysis is often needed [11 14]. It consists of well to tank (WTT) and tank to wheel (TTW) analyses. WTT takes the upstream processes into account and focuses on the fuel production, processing, and delivery, such as oil refinery and electricity generation, in which sophisticated chemical and physical processes are involved. TTW is concerned with energy conversion efficiency from the on board fuel/electricity to the mechanical energy demanded at the wheels. For automotive engineers, TTW is often applied to assess the energy saving capability of a vehicle design and to guide the improvement of the vehicle energy efficiency. In this study, the TTW energy analysis is therefore considered.

One lumped energy efficiency a ratio of the demanded mechanical energy at the wheels to the needed fuel energy was commonly used for the TTW analysis of a vehicle [12,13,15]. This lumped TTW efficiency is well suited for conventional ICE vehicles. Nevertheless, for HEVs or PHEVs with braking energy regeneration, the efficiency may become arbitrarily large, leading to no significance [16].

Another method to describe the TTW analysis of electrified mobility is to characterize each energy conversion process occurring inside the driveline by an averaged efficiency over the driving cycle. For example, energy conversion efficiencies of hybrid electric vehicles with different topologies were investigated by using this

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http://dx.doi.org/10.1016/j.apenergy.2013.06.056

methodology [17 20]. The energy conversion phenomena in PHE Vs were also analyzed by considering the complete energy path [21]. The advantage of the approach is the availability of a thor ough understanding of efficiencies of all the energy conversion steps within the powertrain. However, since the method needs a plethora of distinct efficiencies, the large complexity may be unde sirable to a system level fuel/electricity energy estimation and analysis for HEVs or PHEVs.

Recently, a simple yet useful concept for the TTW analysis was proposed for HEVs [16]. In order to account for the energy recuper ation, the mechanical energy demand at the wheels is viewed as a summation of dissipative energy and circulating energy. Accord ingly, the fuel to traction efficiency and recuperation efficiency are defined to evaluate the TTW process, rather than one lumped efficiency. The novel concept is the most simple and straightfor ward extension of the conventional TTW efficiency, which is mean ingful and applicable to vehicles with energy recuperation. Furthermore, it allows automotive engineers to easily assess the energy effectiveness of electrified powertrains and to find possible solutions with enhanced energy efficiencies from a system level.

The fuel to traction and recuperation efficiencies of a parallel hybrid electric passenger car with an optimal control strategy were analyzed in [16]. However, in the literature, there is a lack of dis cussion on quantification of the two efficiencies for PHEVs, partic ularly on how PHEV energy management strategy and battery size influence them. The purpose of this paper is to analyze the fuel to traction and recuperation efficiencies for a series plug in hybrid electric bus operating in Gothenburg, Sweden. The main contribu tion is twofold: (1) the fuel to traction and recuperation efficien cies of the bus are analyzed and compared for two different optimization based energy management strategies, i.e., the charge depleting and charge sustaining (CD CS) and blended con trols [22 27]. The convex optimization is herein adopted for the two strategies, as it has been certified in our previous work [28 30] that compared to dynamic programming (a benchmark), the convex optimization can accomplish a comparable result with a much lower computational intensity; (2) how downsizing the bus battery affects the two efficiencies is quantified.

The remainder of the paper is organized as follows: Section 2 introduces the bus line and the powertrain model; the definition and the calculation method of the fuel to traction and recupera tion efficiencies are depicted in Section 3; the convex optimiza tion based two energy management strategies for the bus are presented in Section 4; the energy efficiency analysis and compar ison for the two strategies are discussed in Section 5, in which the impact of downsizing the battery on the bus energy efficiencies is evaluated; Conclusions are finally drawn in Section 6.

2. Bus line and powertrain model

The PHEV considered in this study is a bus with a series power train topology [28]. The powertrain does not have a direct mechan ical link between the ICE and the wheels, as shown in Fig. 1. The wheels are propelled by a 220 kW electrical motor (EM, 2200 rpm, and no EM reduction gear) powered by a lithium ion battery pack and/or a 180 kW engine generator unit (EGU). The bus is driven on a bus line in Gothenburg, Sweden, which is de scribed by demanded velocity and road gradient at each point of time (see Fig. 2). The quasi static modeling methodology is em ployed to model the powertrain [5]. The velocity and force de mands of the bus can be translated into an angular velocity x(t) and torque $T_v(t)$ on the shaft between the EM and the final drive, given the demanded acceleration and speed on the bus line and the known vehicle parameters, such as inertia, aerodynamic drag, rolling resistance, and wheel radius.

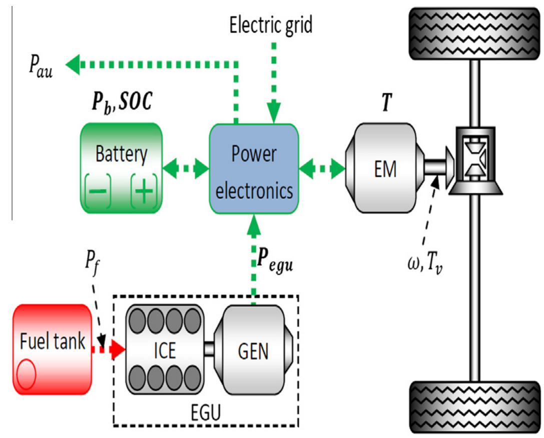

Fig. 1. Powertrain configuration of the plug-in bus.

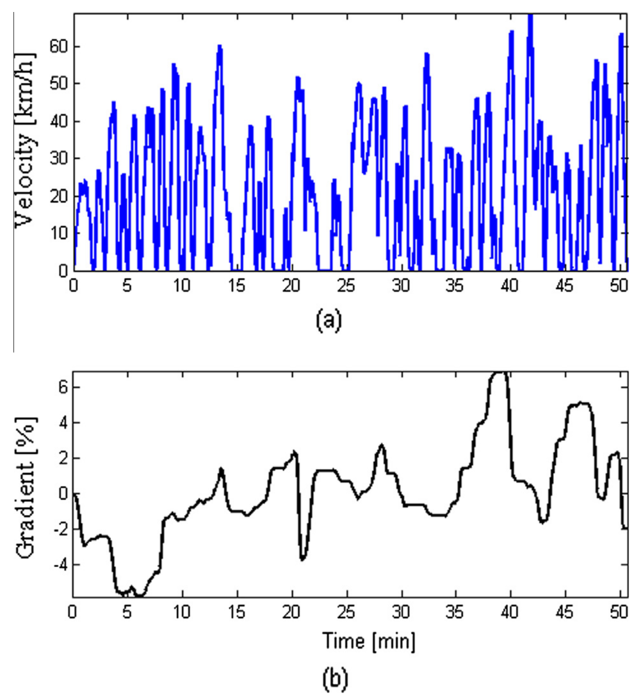

Fig. 2. Driving cycle of the bus line: (a) velocity demand; (b) road gradient.

The EM, which delivers a torque $T(t)$, is designed to be able to meet the high torque demands. Moreover, the EM is also used to recuperate braking energy; when either its torque limit $T_{min}(x(t))$ or the battery charging limit is met, friction braking is supple mented. The power balance equation is described as

$$P_m(t) + P_{loss,m}(t) + P_{au}(t) \quad \boldsymbol{P_b}(t)g_1 + \boldsymbol{P_{egu}}(t)g_{con}, \tag{1}$$

where P_m is the EM power on the shaft between the EM and the fi nal drive calculated by

$$P_m(t) \quad \boldsymbol{T}(t)x(t), \tag{2}$$

and $P_{loss,m}$ is the EM power loss characterized by a quadratic func tion of the motor torque

$$P_{loss,m} \quad b_0(x)\boldsymbol{T}^2 + b_1(x)\boldsymbol{T} + b_2(x), \tag{3}$$

in which b_0, b_1, and b_2 are nonnegative speed dependent coeffi cients. P_{au}, $\boldsymbol{P_b}$, and $\boldsymbol{P_{egu}}$ are the auxiliary power, battery power, and EGU power, respectively. g_{con} is the efficiency of the power con verter (here the averaged efficiency is used, since our focus is on the system level behavior of the powertrain [5,28]), and

$$\begin{cases} g_1 \quad g_{con}, & \boldsymbol{P_b} \geq 0 \\ g_1 \quad \frac{1}{g_{con}}, & \boldsymbol{P_b} < 0. \end{cases} \tag{4}$$

In order to preserve the optimization problem convexity (described later in Section 4), Eq. (1) can be rewritten as

$$P_m(t) + P_{loss,m}(t) + P_{au}(t) \quad \min\left(\boldsymbol{P_b}(t)g_{con}, \frac{\boldsymbol{P_b}(t)}{g_{con}}\right) + \boldsymbol{P_{egu}}(t)g_{con}. \tag{5}$$

The EGU power loss is modeled as a quadratic function of P_{egu}, thereby yielding the fossil fuel (diesel) power

$$P_f(t) \quad a_0\boldsymbol{P}^2_{\boldsymbol{egu}}(t) + (a_1 + 1)\boldsymbol{P_{egu}}(t) + a_2 e(t) \tag{6}$$

with a_i P 0, $i \in \{0, 2\}$. For better readability, we represent all the optimization variables in bold. The binary signal $e(t)$ allows for zero diesel power by removing the idling loss a_2 when the engine is off. $e(t)$ is herein determined by heuristics that turn the engine on if the vehicle power exceeds a threshold P^*_{on}, i.e.,

$$e(t) \quad \begin{cases} 1, & T_V(t)x(t) \geq P^*_{on} \\ 0, & \text{otherwise}. \end{cases} \tag{7}$$

The optimal power threshold P^*_{on} is found by iteratively solving the convex optimization problem for several values of P_{on} within the power range of the vehicle. The detailed procedure can be found in [29], where it has been shown that these heuristics ensure a solu tion close to the global optimum. The efficiencies of the EM and EGU are illustrated in Fig. 3. The quadratic efficiency functions, i.e., Eqs. (3) and (6), are used to preserve the optimization problem convex ity, and details on the validity of using quadratic losses for these components can be found in [29 31].The battery pack consists of n_c consistent cells, where each cell is modeled as a simple resistive circuit. Therefore, the pack power can be described by

$$\boldsymbol{P_b}(t) \quad (V_{oc}(t)I(t) \quad I^2(t)R)n_c, \tag{8}$$

where V_{oc} is the cell open circuit voltage (OCV), I is the cell current, and R is the internal resistance (assumed constant). According to Eq. (8), the current I can be expressed as

$$I(t) \quad \frac{1}{2R}\left(V_{oc}(t) \quad \sqrt{V^2_{oc}(t) \quad \frac{4R\boldsymbol{P_b}(t)}{n_c}}\right) \in [I_{min}, I_{max}], \tag{9}$$

where $[I_{min}, I_{max}]$ is the cell current limits. Additionally, the pack power is limited by

$$\boldsymbol{P_b}(t) \leq \frac{V^2_{oc}(t)n_c}{4R}. \tag{10}$$

The cell OCV $V_{oc}(t)$ is modeled as an affine function of State of Charge (SOC)

$$V_{oc}(t) \quad d_0\boldsymbol{SOC}(t) + d_1, \tag{11}$$

which is a rational approximation within the cell SOC range $[SOC_{min}, SOC_{max}]$ in PHEVs applications, especially for lithium iron phosphate cells, such as A123's ANR26650m1 cell (see Fig. 4). The cell dynam ics is described by

$$\frac{d\boldsymbol{SOC}(t)}{dt} \quad \frac{I(t)}{Q_n}, \tag{12}$$

where Q_n is the cell nominal capacity. A constraint is imposed on the initial SOC

$$\boldsymbol{SOC}(t_0) \quad SOC_0. \tag{13}$$

The main specification of the cell (A123's ANR26650m1) is listed in Table 1, where the internal resistance is an average in the usable SOC range [29,31,40]. Cell packaging and circuitry are assumed to account for 12.3% of the total mass of the battery pack [32]. The main vehicle parameters are shown in Table 2. For simplicity, we assume that there is the constant number of passengers on board. Note that since the bus operates on a specific route and experiences a relatively long time downward slope (see Fig. 2) at the beginning, the battery initial SOC is specified to be 60% rather than 80% to be able to recuperate the initial braking energy.

3. Fuel-to-traction and recuperation efficiencies for plug-in bus

3.1. Dissipative energy and circulating energy

The traction power $P(t)$ that is used to propel the wheels and auxiliary devices of the bus is calculated by

$$P(t) \quad P_{ae}(t) + P_{rol}(t) + P_{au}(t) + P_{ac}(t) + P_{gr}(t), \tag{14}$$

where $P_{ae}(t) = q_{air}A_f c_d v^3(t)/2$ is the power to overcome the aerody namic drag force, with V being the vehicle velocity; $P_{rol}(t) = (m_v + m_p)gc_r\cos(a(t))V(t)$ is the power to overcome the rolling resistance, in which a is the slope, and m_p is the pack mass; $P_{ac}(t) \quad (m_V + m_p)V(t)\frac{dV(t)}{dt}$ and $P_{gr}(t) = (m_v + m_p)g\ \sin(a(t))V(t)$ are

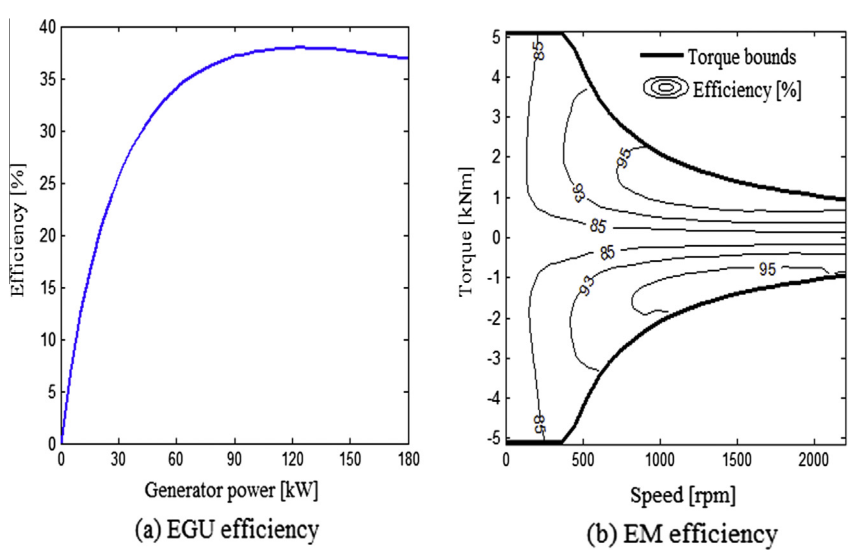

Fig. 3. Efficiencies of the EGU and EM: (a) EGU; (b) EM.

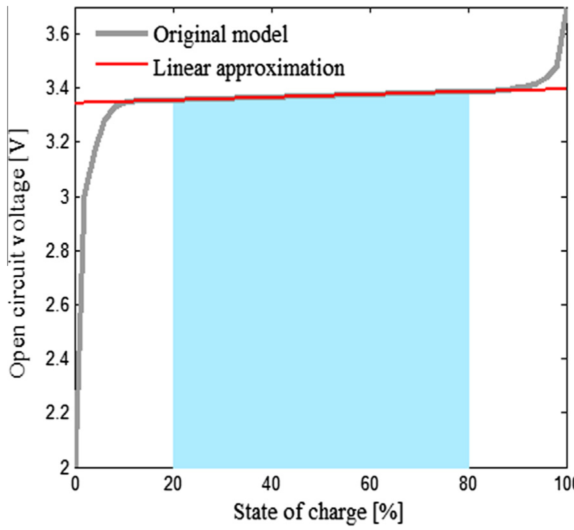

Fig. 4. Cell OCV approximation (A123's ANR26650m1 cell).

Table 1
Li-ion cell specification.

Nominal capacity	Q_n = 8280 As
Nominal voltage	$\overline{V}_{oc}$ 3.3V
Maximum discharging current	I_{max} = 70 A
Maximum charging current	I_{min} = −45 A
Internal resistance	R = 0.01 X
Mass	m_{bc} = 0.07 kg
Coefficient for OCV approximation	d_0 = 0.5 V
Coefficient for OCV approximation	d_1 = 2.95 V

Table 2
Vehicle parameters.

Parameter	Value	Parameter	Value
Frontal area	A_f = 7.54 m^2	Averaged converter efficiency	g_{con} = 98%
Aerodynamic drag coefficient	c_d = 0.7	Final drive efficiency	g_{fd} = 97%
Air density	q_{air} = 1.184 kg/m^3	Diesel price	$c_f = 3.47 \times 10^{\;\;8}$ €/J
Gravity	g = 9.81 m/s^2	Electricity price	$c_{el} = 2.78 \times 10^{\;\;8}$ €/J
Rolling resistance coefficient	c_r = 0.007	Minimum allowable pack SOC	SOC_{min} = 20%
Wheel radius	R_w = 0.509 m	Maximum allowable pack SOC	SOC_{max} = 80%
Final gear	c = 4.7	Initial SOC	SOC_0 = 60%
Vehicle Mass excluding the pack	m_v = 14.5 ton	Base number of cells	n_c = 1000

the powers for acceleration/deceleration and driving uphill/downhill, respectively. $P(t)$ can be split up into two groups: one is the dissipative power $P_{dis}(t) \quad P_{ae}(t) + P_{rol}(t) + P_{au}(t)$; the other is the conservative power $P_{cons}(t) \quad P_{ac}(t) + P_{gr}(t)$ [16]. Since the initial velocity and altitude of the bus are the same as those at the final time in the driving cycle, the integration of the conservative power over the duration of the cycle is equal to zero. If there is a perfect recuperation, the traction energy demand per distance E_{trac} would equal the dissipative energy E_{dis} per distance

$$E_{trac} \quad \frac{\int_{t_0}^{t_f} P(t)dt}{d} \quad \frac{\int_{t_0}^{t_f} P_{dis}(t)dt}{d} \quad E_{dis}, \tag{15}$$

where t_0, t_f, and d are the initial time, final time, and the driving distance in the cycle, respectively. If there is no recuperation (i.e., ICE vehicles),

$$E_{trac} \quad \frac{\int_{P(t)\geq 0} P(t)dt}{d} \quad \frac{\int_{t_0}^{t_f} P_{diss}(t)dt}{d} + \frac{\int_{P(t)<0} \quad P(t)dt}{d}$$
$$E_{dis} + \frac{\int_{P(t)<0} \quad P(t)dt}{d}, \tag{16}$$

where the term $\frac{\int_{P(t)<0} \quad P(t)dt}{d}$ is the circulating energy per distance E_{cir} that is a temporal vehicle energy circulating in the form of kinetic or potential energy and is ultimately dissipated during friction braking. Therefore, Eq. (16) for vehicles without recuperation functionality can be abbreviated as

$$E_{trac} \quad E_{dis} + E_{cir}. \tag{17}$$

In the case of a real recuperation, the following energy balance equation holds

$$E_{trac} \quad E_{dis} + E_{cir} \quad E_{rec}, \tag{18}$$

where E_{rec} is the net energy recuperated that is usable for traction. According to Eqs. (15) and (18), it can be found that the perfect recuperation is $E_{rec} = E_{cir}$.

3.2. Recuperation efficiency

The recuperation efficiency is defined as follows:

$$g_{rec} \quad \frac{E_{rec}}{E_{cir}}. \tag{19}$$

Since E_{cir} can be easily achieved from the driving cycle, the key task is to calculate E_{rec}. The recuperation energy involves two flow ways (i.e., the input and output ways), as shown in Fig. 5. The recuperation capability is governed by the loss of each step, the motor torque limitation, and the lithium ion battery current and charge limitations.

Firstly, we find the time set S such that

$$S \quad \{t | t \in [t_0, t_f], P(t) \quad P_{au}(t) < 0, \boldsymbol{P_b}(t) < 0\}. \tag{20}$$

Note that the auxiliary power demand P_{au} is physically loaded at the converter. The absolute input energy for the set S at the wheels per distance, $E_{w,in}$, is calculated by

$$E_{w,in} \quad \frac{\int_S |P(t) \quad P_{au}(t)|dt}{d}. \tag{21}$$

The associated net energy stored in the battery

$$E_{b,in} \quad \frac{\int_S |P_b(t) + I(t)^2 R n_c|dt}{d}. \tag{22}$$

The resulting energy loss

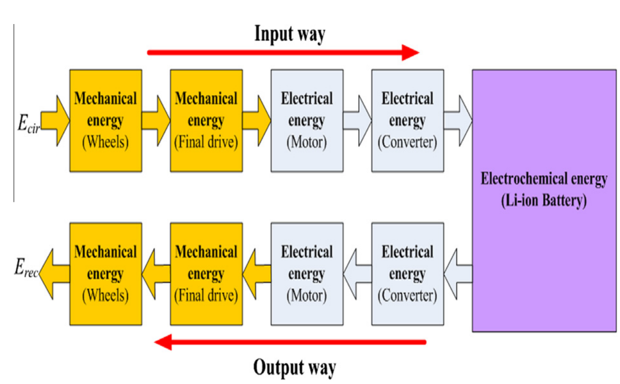

Fig. 5. Schematic of recuperation energy flow of the bus.

$$E_{loss,in} \quad E_{w,in} \quad E_{b,in} \quad \frac{\int_S P_{au}(t)dt}{d}. \tag{23}$$

The cycle averaged wheel to battery energy efficiency can thus be obtained by

$$g_{wb,in} \quad 1 \quad \frac{E_{loss,in}}{E_{w,in}}, \tag{24}$$

yielding the net recuperation energy stored in the battery

$$E_{rec,in} \quad E_{cir} g_{wb,in}. \tag{25}$$

Then, we find the time set D such that

$$D \quad \{t|t \in [t_0, t_f], P(t) \quad P_{au}(t) \geq 0, \boldsymbol{P_b}(t) \geq 0\}. \tag{26}$$

The associated motor energy loss in propelling condition

$$E_{loss,m} \quad \frac{\int_D P_{loss,m}(t)dt}{d}, \tag{27}$$

and the averaged motor efficiency is

$$g_{m,out} \quad 1 \quad \frac{E_{loss,m}d}{\int_D \boldsymbol{P_b}}(t)g_{con} + \boldsymbol{P_{egu}}(t)g_{con} \quad P_{au}(t)dt. \tag{28}$$

The battery energy loss in the time set D

$$E_{loss,b} \quad \frac{\int_D I(t)^2 R n_b dt}{d}, \tag{29}$$

and the corresponding battery efficiency in the output way is

$$g_{b,out} \quad 1 \quad \frac{E_{loss,b}d}{\int_D P_b(t) + I(t)^2 R n_b dt}. \tag{30}$$

The cycle averaged battery to wheel energy efficiency can thus be obtained by

$$g_{bw,out} \quad g_{b,out} g_{con} g_{m,out} g_{fd}, \tag{31}$$

where g_{fd} is the efficiency of the final drive. According to Eqs. (25) and (31), we can acquire the net recuperation energy for traction

$$E_{rec} \quad E_{rec,in} g_{bw,out}, \tag{32}$$

and the cycle averaged recuperation efficiency

$$g_{rec} \quad \frac{E_{rec}}{E_{cir}} \quad g_{wb,in} g_{bw,out}. \tag{33}$$

3.3. Fuel to traction efficiency

The fuel to traction efficiency is defined as

$$g_{ft} \quad \frac{E_{trac}}{E_{ef}} \quad \frac{E_{dis} + (1 \quad g_{rec})E_{cir}}{E_{ef}}, \tag{34}$$

where E_{ef}, termed as the equivalent fuel energy, is the sum of the consumed diesel energy and electric energy per distance. g_{ft} is the cycle averaged conversion efficiency from the total consumed en ergy (diesel and electricity) to the mechanical energy at the wheels and the electrical energy for the auxiliaries. Compared to the elec trical and mechanical paths, the ICE has a far lower efficiency, lead ing to the dominant restriction for g_{ft}. Given Eq. (34), the equivalent fuel energy E_{ef} is obtained by

$$E_{ef} \quad \frac{E_{dis} + (1 \quad g_{rec})E_{cir}}{g_{ft}}. \tag{35}$$

Then, based on the initial and final values of the battery SOC, E_{ef} can be simply split to achieve the individual diesel energy and electricity.

4. Energy management strategies based on convex optimization

4.1. Convex modeling

A convex optimization problem can be written as follows:

$$\begin{aligned} &\text{minimize} && f_0(\boldsymbol{x}) \\ &\text{subject to} && f_i(\boldsymbol{x}) \leqslant 0, \quad i \quad 1, \ldots, m \\ & && h_j(\boldsymbol{x}) \quad 0, \quad j \quad 1, \ldots, p \\ & && \boldsymbol{x} \in V, \end{aligned} \tag{36}$$

where $V \in \mathbb{R}^n$ is a convex set, $f_i(\boldsymbol{x}), i = 0, \ldots, m$, are convex functions, and $h_j(x)$ are affine functions in the optimization vector $\boldsymbol{x}$ [33]. In our studied problem, the optimization variables are $\boldsymbol{T}(t)$, $\boldsymbol{P_b}(t)$, $\boldsymbol{P_{egu}}(t)$, and $\boldsymbol{SOC}(t)$, and the constraints are vehicle power balance, i.e., Eq. (5), and the battery constraints Eqs. (9) (13). It is easy to notice that Eqs. 5, 9, and 10 do not comply with the definition of a convex problem. Eq. (5) can be written as convex, by relaxing the equality to inequality; it has been suggested in [34] that Eqs. (9) and (10) can be reformulated as convex functions by introducing a new variable

$$\boldsymbol{E}(t) \quad \frac{CV_{oc}^2(t)n}{2} \tag{37}$$

with $C \quad \frac{2Q_n}{V_{oc}}$. The resulting convex constraints are then given as

$$P_m(t) + P_{loss,m}(t) + P_{au}(t) \leqslant \min\left(\boldsymbol{P_b}(t)g_{con}, \frac{\boldsymbol{P_b}(t)}{g_{con}}\right) + \boldsymbol{P_{egu}}(t)g_{con}, \tag{38}$$

$$\boldsymbol{P_b}(t) \text{ P } \sqrt{\frac{2\boldsymbol{E}(t)n_c}{C}} I_{\min} \quad RI_{\min}^2 n_c, \tag{39}$$

$$\boldsymbol{P_b}(t) \leqslant \frac{\boldsymbol{E}(t)}{2RC}, \tag{40}$$

$$\boldsymbol{E}(t) \quad \sqrt{\boldsymbol{E}^2(t) \quad 2RC\boldsymbol{E}(t)\boldsymbol{P_b}(t)} \leqslant I_{\max}R\sqrt{2CE(t)n_c}, \tag{41}$$

$$\frac{d\boldsymbol{E}(t)}{dt} \leqslant \quad \frac{d_0}{RQ_n}(\boldsymbol{E}(t) \quad \sqrt{\boldsymbol{E}^2(t) \quad 2\boldsymbol{R}CE(t)\boldsymbol{P_b}(t)}), \tag{42}$$

$$\boldsymbol{E}(t) \in \frac{C}{2}[V_{oc}^2(SOC_{\min}), V_{oc}^2(SOC_{\max})]n_c, \tag{43}$$

$$\boldsymbol{E}(t_0) \quad \frac{C}{2}V_{oc}^2(SOC_0)n_c. \tag{44}$$

4.2. Energy management strategies

As opposed to HEVs, the battery charge in PHEVs is used. The optimal energy control strategy for PHEVs is often defined to min imize the equivalent fuel cost (i.e., liquid fuel and electricity). For trips shorter than the all electric range (AER), PHEVs are equivalent to battery electric vehicles (BEVs), and the associated optimal en ergy control charge depleting (CD) mode is deployed, since elec tricity is considerably cheaper than liquid fuel [35]. The optimal strategy in this case is trivial [35 37]. The discussed plug in hybrid electric bus has a fixed driving route longer than the AER, which gives a degree of freedom concerning the optimal power split be tween the battery and the EGU. Otherwise, it will become a battery electric bus that typically needs considerably larger and more expensive battery pack. Two feasible energy management strate gies, based on convex optimization, are considered. One is the CD CS strategy for which the bus firstly operates in CD mode until the battery charge arrives at a pre specified threshold and then switches to convex optimization based CS mode; the other is the blended strategy, implying that the optimal power allocation be tween the battery and the EGU is attained throughout the route by convex optimization. The two strategies are formulated in Ta ble 3. In order to guarantee a fair comparison, the final battery SOC for the two strategies should be identical. The natural and straightforward form of the convex optimization problem is auto matically parsed by a tool, CVX [33,38], so as to derive a general

Table 3
Two energy management strategies for the plug-in bus.

Convex-optimization-based energy management
1. CD–CS strategy
(1) CD Phase (no optimization)
For $k = 1, \ldots, N_{cd}$, with $SOC(N_{cd}+1)$ corresponding to the switching SOC (25% in our case)
(a) Solve the cell current $I_0(k)$ algebraically, according to the calculated battery power $P_{b,0}$ without considering the cell current and charge limitations:
$T_{(k)} \in [T_{min}(x(k)), T_{max}(x(k))],\ \ P_m(t)+P_{loss,m}(t)+P_{au}(t) \quad \min\left(P_{b,0}(t)g_{con}, \frac{P_{b0}(t)}{g_{con}}\right),$
$I_0(k) \quad \frac{V_{oc}(k) \quad \sqrt{V_{oc}^2(k) \quad \frac{4P_{b0}(k)}{n_cR}}}{2R}.$
(b) Achieve the correct cell current $I(k)$, considering the cell current and charge limitations:
$I(k) \in [I_{min}, I_{max}],\ \ SOC(k+1) \quad SOC(k) - \frac{I(k)Dt}{Q_n}, SOC(k) \in [SOC_{min}, SOC_{max}]$.D$t$ is the time interval.)
(c) Calculate the correct battery power $P_b(k) = V_{oc}(k)I(k)n_c - I^2(k)Rn_c$, $SOC(k)$, $E(k)$, and $T(k)$. Note that the above limitations are only active when the friction braking is needed.
(2) CS Phase (convex optimization)
For $k = N_{cd} + 1, \ldots, N$, with N corresponding to the final time step
Variables: $P_b(N-N_{cd})$, $P_{egu}(N-N_{cd})$, $E(N+1-N_{cd})$, $T(N-N_{cd})$ (the number in parentheses is the vector length)
Expressions: $P_f(N-N_{cd})$, $P_m(N-N_{cd})$, $P_{loss,m}(N-N_{cd})$, $J_c \quad \sum_{k=N_{cd}+1}^{N} c_f P_f(k)Dt$
Minimize J_c
Subject to Eqs. (38)–(43), $E(N_{cd}+1) = E(N+1)$, $T(k) \in [T_{min}(x(k)), T_{max}(x(k))]$, $P_{egu}(k) \in [0, P_{max,egu}]$, $P_{egu}(e_{off}) = 0$ (e_{off} is an index vector of $e(k) = 0$, indicating the engine-off steps.)
2. Blended strategy (convex optimization)
For $k = 1, \ldots, N$, with N corresponding to the final time step
Variables: $P_b(N)$, $P_{egu}(N)$, $E(N+1)$, $T(N)$
Expressions: $P_f(N)$, $P_m(N)$, $P_{loss,m}(N)$, $J_c \quad \sum_{k=1}^{N} c_f P_f(k)Dt + c_{el}(SOC_0 - SOC_f)Q_n\overline{V}_{oc}n_c$
Minimize J_c
Subject to Eqs. (38)–(44), $E(N+1) \quad \frac{C}{2}V_{oc}^2(SOC_f)n_c$, $T(k) \in [T_{min}(x(k)), T_{max}(x(k))]$, $P_{egu}(k) \in [0, P_{max,egu}]$, $P_{egu}(e_{off}) = 0$

semi definite program (SDP) form. The bold variables are parameters to optimize (see Section 4.1). Note that the so called expressions in the table are not equality constraints, but are merely used for better readability. CVX substitutes the expressions with the corresponding mathematical operations. After these, the problem is passed to the solver, SeDuMi [39,40], to obtain the optimal variables with high computational efficiency. Since the optimization problem is convex, instead of trapping into local minima, a global optimization solution can be rapidly accomplished, with any initialization. Please refer to [33] to find more details on the theoretical and algorithmic properties of convex optimization.

5. Results and discussion

5.1. Efficiency analysis and comparison of the two energy control algorithms

Given the driving cycle and the optimal variables extracted by the foregoing algorithms, the recuperation and fuel to traction efficiencies can be calculated, as Section 3 describes. Before discussing the two efficiencies, it is important to investigate the operating states of the power sources (the battery and the EGU) in the powertrain. The cell SOC and current distribution for the two strategies are shown in Fig. 6. It is clear that both the average and maximum absolute cell currents in the blended algorithm are smaller than those in the CD CS algorithm, leading to less battery energy loss. Observing the SOC trajectory, we can further conclude that the current difference is mainly existent in the discharging process. The round trip battery efficiency and the recuperation efficiencies in the input and output directions are shown in Fig. 7. Compared to the CD CS strategy, the blended scenario has obviously higher averaged battery efficiency (by 1.73%) and recuperation efficiency in the output way (by 1.32%), because of much smaller discharging current. A slightly better recuperation efficiency in the input way is also observed for the blended algorithm, because cells have a slightly higher OCV (see Figs. 4 and 6) during charging and thus a little smaller energy loss, given the same charging power. The EGU efficiencies for the two strategies are similar, as shown in

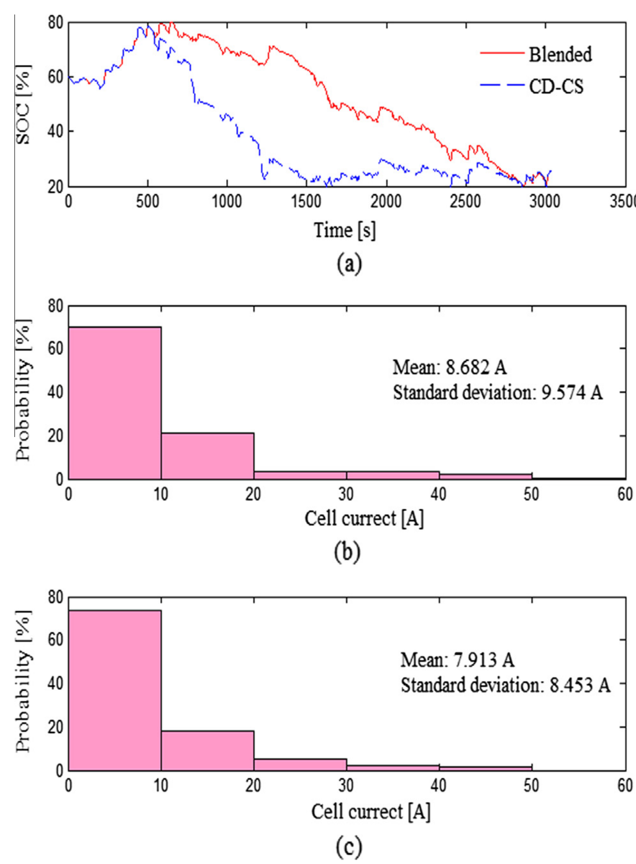

Fig. 6. (a) SOC trajectories, (b) absolute current distribution in the CD–CS strategy, and (c) absolute current distribution in the blended strategy.

Fig. 8, since the convex optimization is used to determine the optimal EGU power in both strategies. The recuperation efficiency, fuel to traction efficiency, and energy consumption per kilometer are shown in Fig. 9. The recuperation efficiency for the CD CS strategy is 64.86%, while that for the blended strategy is 66.13% an improvement of 1.27% mainly resulting from the battery current deviation. The fuel to traction efficiency for the CD CS strategy is 35.83%, while that for the blended strategy is 36.13% an improve ment of 0.3%. The fuel to traction efficiency is mainly limited by the EGU efficiency (see Fig. 8) and also affected by energy losses occurring in other electrical and mechanical paths, e.g., battery, power converter, electric motor, and final drive. The energy con sumption per kilometer for the CD CS strategy is 9.02 MJ, while that for the blended strategy is 8.87 MJ an improvement of 0.15 MJ. Since both strategies consume the same amount of elec tricity, the blended strategy can save diesel energy of 0.15 MJ per kilometer, which is attributed to the superior recuperation and fuel to traction efficiencies. It is worth mentioning that since the transit bus runs approximately 50,000 km per year (much longer than standard passenger cars), the energy saving caused by the more advanced blended strategy is significant.

5.2. Impact of battery downsizing on the bus energy efficiency

In addition to a better TTW energy conversion, Section 5.1 shows that the blended energy control algorithm needs less bat tery discharging power, inducing a potential of reducing the bat tery size. As lithium ion battery is still highly costly in the market and is the most expensive component in the bus power train, downsizing is of great significance for decreasing the pur chase cost of the bus. However, it is necessary to assess the influence of battery downsizing on the recuperation and fuel to traction efficiencies of the plug in bus. Given the reduced battery sizes, the round trip battery efficiency and the recuperation effi ciencies in the input and output directions are shown for the opti mal blended strategy in Fig. 10. It is notable that all the three efficiencies become lower with the battery downsizing. In particu lar, the recuperation efficiency in the input way has a dramatic

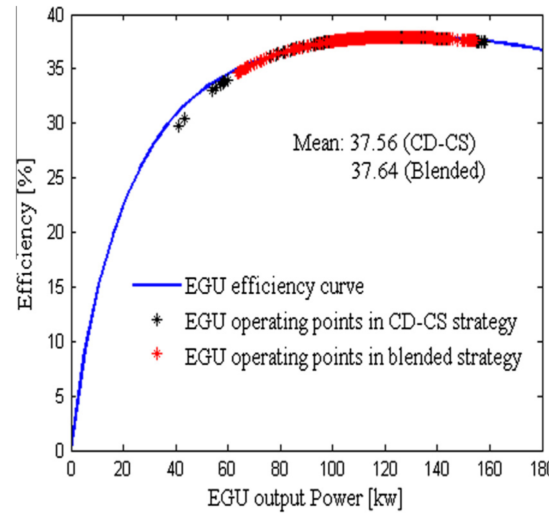

Fig. 8. EGU efficiencies.

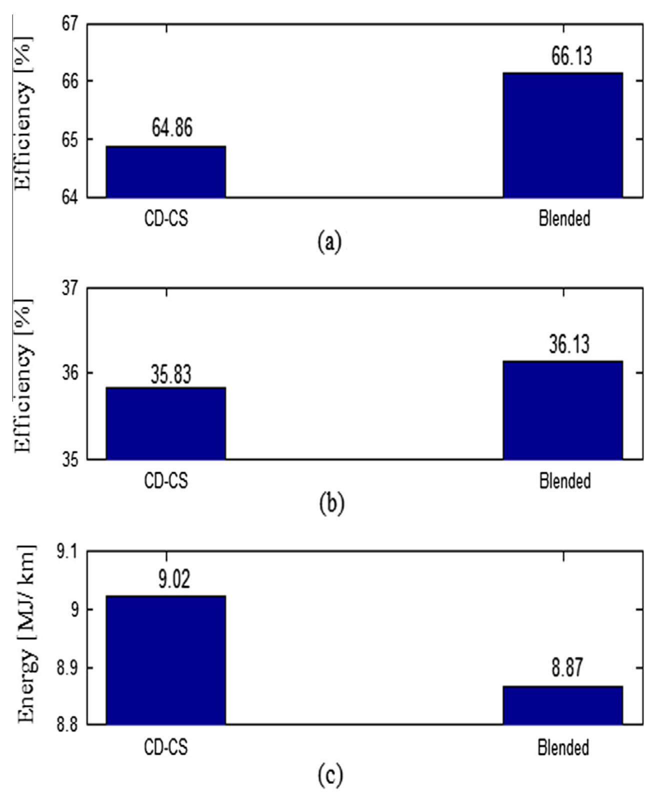

Fig. 9. (a) Recuperation efficiency (two-way), (b) fuel-to-traction efficiency, and (c) energy consumption per distance.

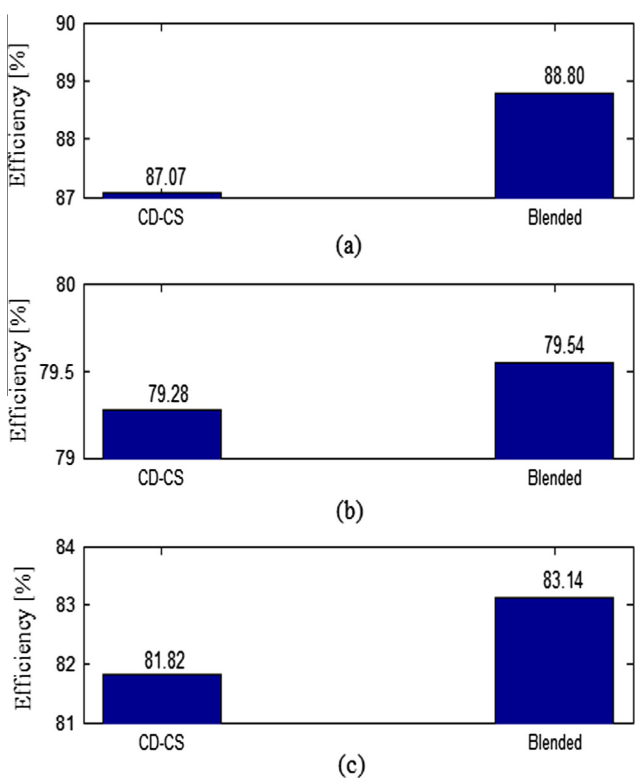

Fig. 7. (a) Round-trip battery efficiency, (b) recuperation efficiency in the input way, and (c) recuperation efficiency in the output way.

drop, since the battery current has an evident increase during recu peration when the engine is off, and the friction braking is more likely to be used to meet the current and charge limitations.

The associated impact on the recuperation efficiency, fuel to traction efficiency, and energy consumption per kilometer are shown in Fig. 11. It can be found that the battery downsizing has an apparently negative effect on the recuperation efficiency of the bus. The fuel to traction efficiency also decreases with the re duced battery size. Owing to the deterioration of the two efficien cies, the energy consumption per kilometer increases. Therefore, there is a tradeoff between battery downsizing and energy effi ciency. The battery should be downsized with a careful consider

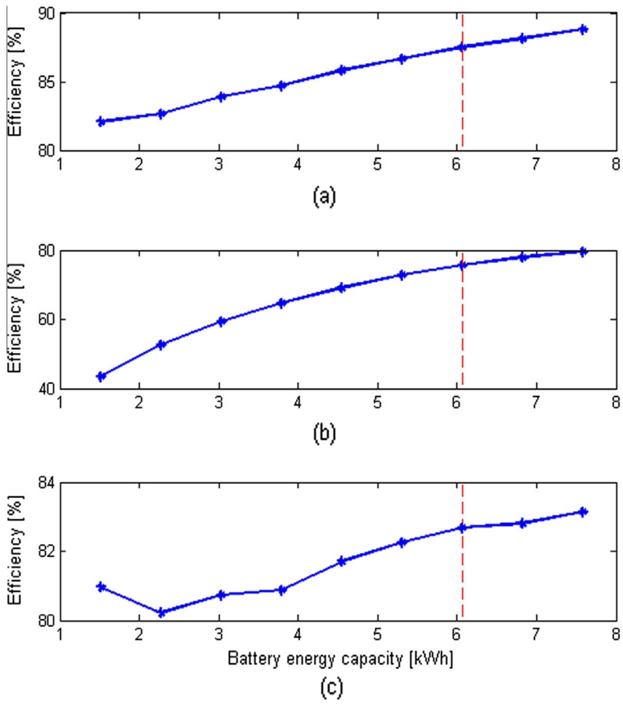

Fig. 10. Efficiency versus battery size: (a) round-trip battery efficiency; (b) recuperation efficiency in the input way; (c) recuperation efficiency in the output way.

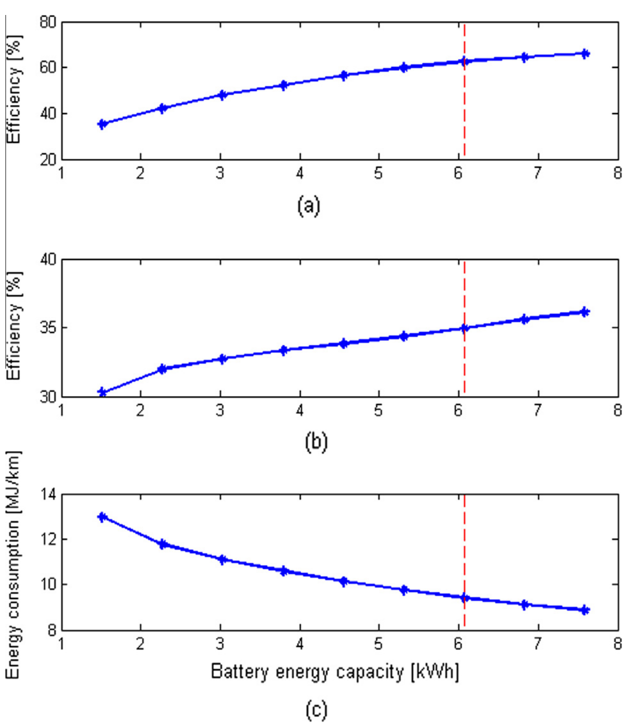

Fig. 11. Efficiency versus battery size: (a) recuperation efficiency (two-way); (b) fuel-to-traction efficiency; (c) energy consumption per distance.

ation without sacrificing the two efficiencies to an unacceptable degree. For example, if the recuperation and fuel to traction efficiencies are required not to be less than 63% and 35%, respectively, there will be a possibility of reducing the pack by 1.52 kW h. On the other hand, from a viewpoint of cost, the tradeoff is between the purchase cost and the operating cost, and the total ownership cost (TCO) should thus be considered. However, it is not trivial to find the best solution, since TCO depends on a variety of factors, such as diesel price, electricity price, battery price, total bus mileage, and battery replacement.

6. Conclusions

This paper analyzes the TTW energy conversion efficiency of a series plug in hybrid electric bus operating in Gothenburg, Sweden. The TTW process is characterized by the recuperation and fuel to traction efficiencies, which are quantified and compared for two optimization based energy management strategies, i.e., the CD CS and blended energy controls. The convex modeling of the bus powertrain is performed, and the efficient convex optimization is used for the two strategies. The efficiency analysis indicates that the recuperation efficiencies for the CD CS and blended strategies are 64.86% and 66.13%, respectively; the fuel to traction efficiencies are 35.83% and 36.13%; the diesel energy consumptions per kilometer are 9.02 MJ and 8.87 MJ. The blended algorithm thus leads to a more efficient TTW energy conversion of the plug in bus. Considering the potential of downsizing the battery for the blended algorithm that requires less battery discharging power, we also quantify the impact of battery downsizing on the recuperation and fuel to traction efficiencies and the energy consumption per kilometer. It can be found that as the battery energy capacity decreases, the two efficiencies become worse. There is, therefore, a tradeoff between the battery downsizing and energy efficiencies for the plug in bus with the blended energy management strategy.

Acknowledgement

This work was supported by Swedish Energy Agency.

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