

Article

Development of an Energy Consumption Minimization Strategy for a Series Hybrid Vehicle

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Abstract

Due to the limitations of current battery technologies—such as lower energy density and high cost compared to fossil fuels—electric vehicles (EVs) face constraints in applications requiring extended range or heavy payloads, such as refuse trucks. As a midterm solution, hybrid electric vehicles (HEVs) combine internal combustion engines (ICEs) and electric powertrains to enable flexible energy usage, particularly in urban duty cycles characterized by frequent stopping and idling. This study introduces a model-based energy management strategy using the Equivalent Consumption Minimization Strategy (ECMS), tailored for a retrofitted series hybrid refuse truck. A conventional ISUZU NPR 10 truck was instrumented to collect real-world driving and operational data, which guided the development of a vehicle-specific ECMS controller. The proposed strategy was evaluated over five driving cycles—including both standardized and measured urban scenarios—under varying load conditions: Tare Mass (TM) and Gross Vehicle Mass (GVM). Compared with a rule-based control approach, ECMS demonstrated up to 14% improvement in driving range and significant reductions in exhaust gas emissions (CO, NO_x, and CO₂). The inclusion of auxiliary load modeling further enhances the realism of the simulation results. These findings validate ECMS as a viable strategy for optimizing fuel economy and reducing emissions in hybrid refuse truck applications.



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1. Introduction

Even though the idea of a HEV is not new; -the first hybrid design patent goes back to the 1900s- today's hybrids look and operate very differently from their predecessors. The aim of increasing overall efficiency and lowering emission levels has led to different hybridization, resulting in various architectures: series, parallel, series-parallel, and complex hybrid. Since there is no universal architecture that can be considered superior in all aspects (e.g., efficiency, range, performance, cost, weight), the decision process regarding HEV architecture is crucial in achieving performance targets and to fulfill the distinct requirements of different transport segments. While parallel hybrid vehicles (PHEVs) are generally preferred for performance, series hybrid vehicles (SHEVs) offer advantages in urban applications like refuse trucks. This study builds upon that rationale by converting a conventional refuse truck to a series hybrid configuration and designing a tailored ECMS

controller based on real-world driving data. In the series architecture, the internal combustion engine (ICE) is decoupled from the wheels and supplies power to the traction motor through an electric generator (EG) to drive the vehicle. In contrast to series architecture, in the parallel configuration, both the ICE and electrical machine (EM) are connected to the road wheels in parallel [1]. Both can provide the tractive power to drive the vehicle through the axles they are coupled to. The battery pack (BP) can supply power for traction, or aid the engine in driving the vehicle [2].

In [2], a rule-based energy management strategy was applied using the energy distribution method in serial hybrid vehicles. The results were compared with the most common strategy, the thermostat control. In [3], the model predictive control model was developed for the first time as a solution to the energy management strategy problem of the series hybrid bulldozer. Field working conditions were taken into consideration. The results were compared with a rule-based model and a dynamic programming model, and it was observed that it saved fuel with a six percent difference compared to the rule-based model. In [4], a rule-based strategy has been developed using an efficiency map of a generator. Depending on the State of Charge (SOC), it is recommended that the generator be kept on or on/off. It provides the value of the average power that the source should supply and the amount of power fluctuation to be monitored to minimize system consumption. The thermostat control strategy is a rule-based strategy in which the on/off state of the engine is determined by the upper and lower limits of the battery SOC [5]. In comparison with thermostat control, an efficiency increase between 1.6% and 5% was observed. HEV fuel economy and emission improvements mostly depend on the energy management strategy. Theoretically, dynamic programming is a suitable technique to optimally solve control problems. However, dynamic programming requires prior knowledge of the drive cycle, making it unsuitable for the real-time controlled HEVs [6].

Optimization-based methods deliver optimal results in terms of fuel consumption. Fuel consumption is defined as a cost function that is minimized for a given drive cycle by mathematical optimization. Map-based models are often used for this purpose, taking into account the fuel consumption of the combustion engine and the energy efficiency of the electric drive through corresponding maps. Typical numerical methods for optimization-based in the literature are Pontryagin's Maximum Principle (PMP) [7,8], Particle Swarm Optimization (PSO) [9], Sequential Quadratic Programming (SQP) [10], and Dynamic Programming (DP) [11,12]. Another method is to use an analytical powertrain model instead of a map-based approach [13]. These approaches are often simple polynomials and allow the optimization problem of the operating strategy to be solved analytically using PMP [14–18].

In [19], they presented an online ECMS controller for a fuel cell-powered heavy-duty truck. The study eliminated the need for a priori calculations by integrating a dynamic forward-facing simulation model with a kinematic backward-facing surrogate model. This approach allowed for real-time optimization and significant workflow improvements. The ECMS controller, implemented on regulatory cycles, demonstrated the potential for substantial fuel savings and efficient energy management. Another study explored the application of an adaptive-ECMS for hybrid electric vehicles with continuously variable transmissions (CVTs). Their study introduced a real-time control strategy incorporating learning vector quantization (LVQ) for driving pattern recognition. The adaptive-ECMS adjusted the equivalent factor based on driving patterns and battery state of charge (SOC), improving fuel consumption and drivability. This approach minimized frequent engine on/off events and large variations in CVT speed ratio, enhancing overall vehicle performance [20]. Another significant contribution is from researchers at RWTH Aachen University, who developed an advanced ECMS for hybrid electric heavy-duty trucks. This strategy employs predictive

battery discharge and an adaptive operating strategy that considers road slope and vehicle mass. Their findings showed that the proposed EMS could achieve up to 2% fuel savings compared to heuristic strategies. This research underscores the importance of intelligent energy management in optimizing the performance and efficiency of heavy-duty trucks under real-world driving conditions [21].

Despite significant advancements in hybrid electric vehicle (HEV) technologies, the energy management strategies for refuse trucks have not been extensively explored. The existing literature primarily focuses on passenger vehicles and general-purpose HEVs, often neglecting the unique operational patterns of refuse trucks, which involve frequent stopping, idling, and variable load conditions. These characteristics result in higher energy consumption and emissions, which are not adequately addressed by conventional energy management strategies. This study presents a novel approach to transforming a conventional truck (ISUZU NPR 10) into a series hybrid refuse truck and optimizing its performance using a vehicle-specific Equivalent Energy Consumption Minimization Strategy (ECMS). Initially, a conventional truck was operated over real-world driving (see Figure 1) to collect comprehensive GPS data (speed, latitude, longitude, altitude) and sensor data (shaft speed, power consumption, engine temperature). This data provided a robust baseline for analysis and comparison.



Figure 1. Real-world track in Istanbul. The red line represents the actual driving route of the test vehicle during data collection.

In this study, a conventional ISUZU NPR 10 diesel-powered refuse truck was converted into a series hybrid configuration through a structured retrofitting process. The internal combustion engine and transmission system were removed, and replaced by a six-phase electric traction motor, whose magnetic, thermal, and mechanical characteristics were evaluated using detailed design reports. A newly developed six-phase motor inverter (motor driver) was integrated to control the traction system. For energy generation, a three-phase generator set (GENSET) was included, driven by a secondary downsized internal combustion engine, and paired with a custom-designed motor driver. Additionally, a high-voltage power distribution unit (PDU), onboard charging system, and an auxiliary load energy management algorithm were developed to complete the vehicle's electrification. The overall system was designed in accordance with ISO 26, 262 standards [22] to ensure functional safety. Leveraging the collected data and using the maps of the internal combustion engine provided by the Cummins, a vehicle-specific ECMS control strategy was developed to optimize energy consumption. The ECMS dynamically balances the use of fuel and electrical energy, tailored to the unique operational patterns of refuse truck duties. The test vehicle used in this study is a retrofitted ISUZU NPR 10 refuse truck (see

Figure 2), equipped with custom sensors and a hybrid powertrain for data acquisition and control validation.



Figure 2. Series hybrid refuse truck used for real-world data collection and controller prototyping.

While ECMS has been widely studied, its specific application to refuse trucks, which have unique operational patterns (frequent stops and idling), represents a novel contribution. Adapting and optimizing ECMS for this particular use case can demonstrate significant improvements in fuel efficiency and emissions reduction. Providing a detailed analysis of the environmental and economic benefits of implementing ECMS in refuse trucks, such as reductions in greenhouse gas emissions, fuel savings, and cost-effectiveness over the vehicle's lifecycle, can be a novel contribution. Highlighting these impacts can strengthen the case for broader adoption of this technology.

The novel contributions of this study are summarized as follows:

- A conventional ISUZU NPR 10 refuse truck was retrofitted into a series hybrid vehicle configuration by replacing the internal combustion engine with an electric motor and generator setup.
- Real-world driving and operational data were collected from the original ICE-powered vehicle and used to design and tune a vehicle-specific ECMS controller.
- The proposed ECMS was evaluated under five driving cycles with different load scenarios (Tare Mass and Gross Vehicle Mass), and its performance was benchmarked against a rule-based controller.
- Unlike most ECMS studies focused on passenger cars, this study addresses the unique operational characteristics of refuse trucks, including frequent stopping, idling, and auxiliary energy demands, making it one of the few targeted investigations in this segment.

Accordingly, the paper is organized as follows. First, the introduction is given. This is followed by Section 2, where hypothetical vehicle architecture, powertrain components, and auxiliary load mathematical models are presented. In Section 3, the proposed control strategy is explained in detail. In Section 4, simulation results are given and compared with the rule-based controller in terms of energy consumption and emissions. In the final section, the paper is concluded with a discussion of the results.

2. Configuration and Models of SHEV

SHEV is a vehicle configuration in which ICEs are connected in series with EMs, and only electric machines drive the vehicle wheels. The ICE is connected to the generator through a shaft and used in the production of electrical energy. The electrical energy

produced by ICE is stored in the batteries. This electrical energy provides acceleration to the vehicle by using the EM, which is connected to the wheels. As shown in Figure 3, the ICE is connected to a generator, and the produced energy is used to power the electric motors via the battery.

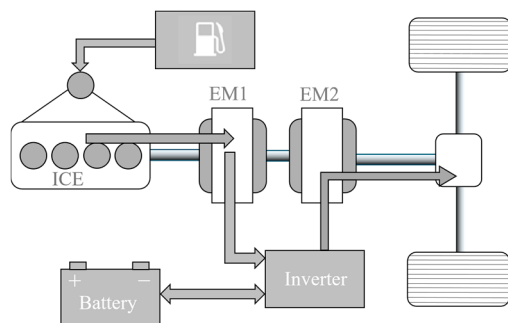


Figure 3. The working principle schematic of the SHEV is represented [23].

2.1. Vehicle Dynamic Models

The vehicle's propulsion system should overcome the resistive forces. These resistive forces are expressed as follows: the tractive force F_t supplied by the electrical motor must be able to overcome the aerodynamic F_{aero} , rolling F_r and grade F_{hc} resistances for the vehicle to move [24,25]. The equation of motion can be written as:

$$F_t = F_{aero} + F_r + F_{hc} + F_{acc} \quad (1)$$

$$F_t = mg\mu_r \cos a + mg \sin a + \frac{1}{2} \rho C_x A v^2 + m \frac{dv}{dt} \quad (2)$$

In (1), F_{acc} is the inertial force. In (2), m is the vehicle mass, μ_r is the rolling resistance coefficient, a is the gradient angle, ρ is the density of air, C_x is the air resistance coefficient, A is the frontal area, and v is the vehicle velocity.

2.2. EM Model

All types of electrical machines are used in HEVs, and most preferred Brushless Direct Current Motor (BLDC), asynchronous, and Switched Reluctance machines [26]. The mathematical model of BLDC can be implemented in the MATLAB®/Simulink mechanical toolbox environment, or a torque–speed characteristic map of the EM can be modeled using a look-up table. EM efficiency is also a function of torque T_{em} , and speed n_{em} .

The relationship between motor torque, speed, and throttle input can be represented by a 3D map, which defines the performance characteristics of the electric motor under varying load conditions, as illustrated in Figure 4. The shading (or color gradient) in the figure represents the torque magnitude.

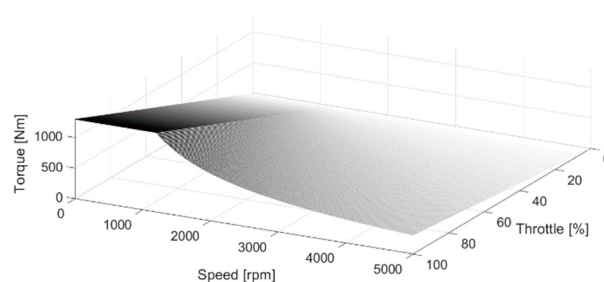


Figure 4. Shows the output torque, speed, and throttle signal map of EM system.

2.3. ICE Model

It is usually represented by an appropriate two-dimensional lookup table, instead of an analytical model. Studies to create dynamic models for calculating fuel consumption can be found in the literature. It was proposed in [27] to determine fuel consumption, Q_s , measured in liters per 100 km via the following equation:

$$Q_s = \frac{g_e \cdot (P_{rl} + P_w + P_a)}{10 \cdot v \cdot \eta_T \cdot \rho_f} \quad (3)$$

where g_e is the optimal specific fuel consumption, P_{rl} is the rolling resistance of the road, P_w is the power required to overcome the resistance of the air, P_a is the power required to overcome the resistance of the inertial acceleration, η_T is the efficiency of the transmission, ρ_f is the fuel density, and v is the average speed of the vehicle. Instead of using the analytical fuel consumption model given in (3), a map-based ICE model was utilized for higher accuracy and reduced computational burden. Figure 5 demonstrates the fuel consumption map based on engine torque and speed inputs.

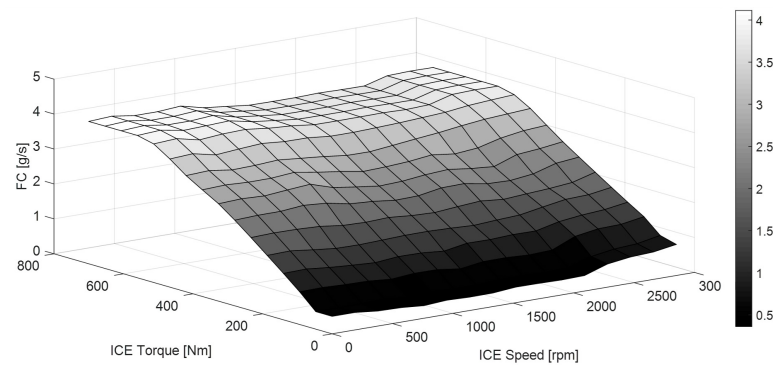


Figure 5. ICE fuel consumption map is presented for illustration.

2.4. Battery Model

In this study, a lithium-ion battery model based on Nickel Manganese Cobalt Oxide (NMC) chemistry was used. NMC batteries are commonly preferred in automotive hybrid applications due to their favorable balance between energy density, cycle life, and thermal stability. The model includes SOC-dependent efficiency, and charging/discharging power limits based on typical NMC battery ratings. Although degradation and temperature effects were not modeled, future work will incorporate lifetime-aware control constraints to evaluate long-term battery performance. To better represent OCV behavior, a term related to polarization voltage is added and the term related to polarization resistance [28–30] is slightly modified. The battery voltage obtained is given by:

$$E_{Batt} = E_0 - R_{polar} \cdot i_{filter} - R_{polar} \cdot \frac{Q}{Q - Q_{used}} \cdot Q_{used} + K_A \cdot e^{(-K_B \cdot Q_{used})} \quad (4)$$

The percentage of battery SOC can be predicted by Q_{used} , which is the total current:

$$SOC = 100(1 - \frac{1}{Q} \int_0^t i(t) dt) \quad (5)$$

where E_{Batt} is the battery voltage, E_0 is the OCV, R_{polar} is the polarization resistance, i_{filter} is the filtered battery current, Q is the total capacity, K_A is the voltage drop in the exponential zone, K_B is the time constant of the exponential zone, and SOC is the state of charge.

2.5. Auxiliary Load Model

In HEV studies in the literature, the energy consumption of the auxiliary systems in the vehicles is seldom addressed. While the total power of the auxiliary system loads is less than 10% of the driving power when accelerating, it can be close to 30% of the average load power when cruising [31,32]. Therefore, the power of auxiliary loads should be included in the simulation modeling for more accurate energy analysis. In a conventional vehicle, where the crankshaft drives most auxiliary systems via a belt or a gear pinion, the energy consumption of the auxiliary loads is less apparent. In a hybrid electric vehicle, the energy must first be converted to electricity and thus the consumption is more apparent. The energy consumption of auxiliary systems is heavily dependent on the vehicle topology selection, the control strategies, and the drive cycles [32].

Figure 6 shows the real measurements of power consumed by the pneumatic system during a typical refuse collection cycle. In the Kadıköy municipality of Istanbul, an average refuse collection cycle involves approximately 40–50 refuse pick-up events. The pneumatic system demands the most power among the auxiliary loads in refuse trucks. Therefore, it must be included in the energy calculations.

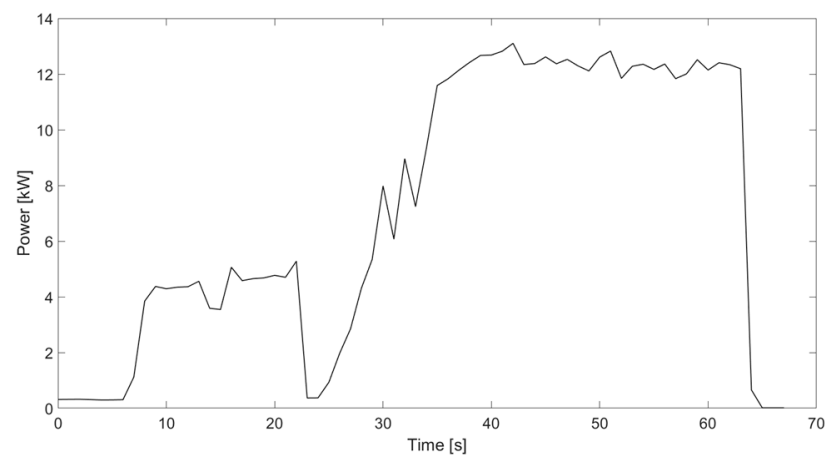


Figure 6. Refuse collection power consumption.

Figure 1 shows the complete GPS-based driving trajectory collected during the real-world operation of the conventional refuse truck in Istanbul. During this route, the vehicle performed multiple refuse collection events, each typically lasting around 65 s. Figure 6 presents the measured auxiliary power consumption corresponding to one such average refuse collection event, including bin lifting, compacting, and hydraulic actuation. This waveform, obtained via onboard power measurement equipment, was incorporated into the simulation model to realistically reflect auxiliary power demand. Integrating this data allowed the ECMS controller to optimize energy use not only for propulsion but also for auxiliary system loads, resulting in a more accurate simulation of urban refuse truck operation.

2.6. System Architecture

The structure of the series hybrid system is shown in Figure 7, which mainly includes the ICE-generator set, battery pack, electrical motor, and energy management system (EMS).

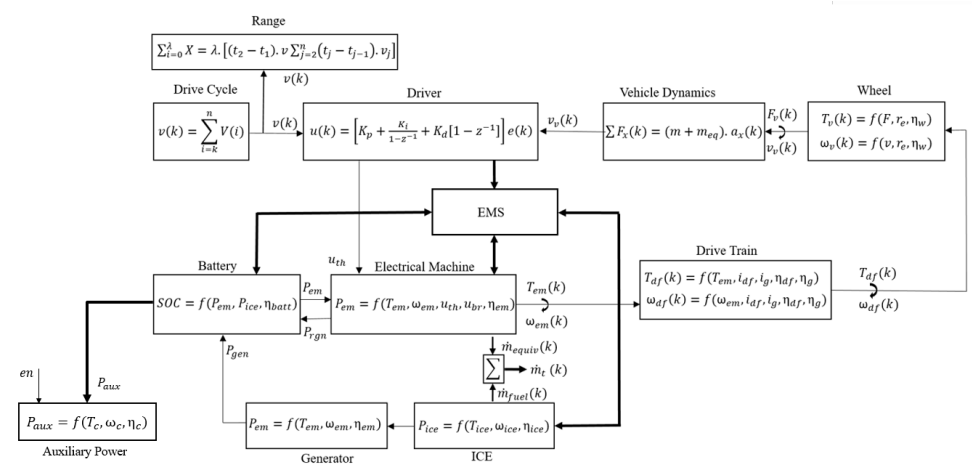


Figure 7. Series HEV powertrain layout scheme.

The basic parameters of the vehicle are given in Table 1. Since it is a refuse truck, its weight varies significantly.

Table 1. Vehicle parameters.

Parameter	Value	Unit
Vehicle Mass	6800, 13,800	kg
Tire Radius	0.38	m
Frontal Area	4.8	m ²
Rolling Resistance Coeff.	0.0063	-
Aerodynamic Drag Coeff.	0.68	-
Differential Ratio	4.77	-
EM Power	150 (Cont.)	kW
ICE Power	134	kW
Battery Nominal Voltage	600	V
Battery Capacity	42	Ah

3. Problem Description

3.1. Pontryagin's Minimum Principle

In a dynamic system described by a set of ordinary differential equations representing the state $x(t)$ and the control input $u(t)$,

$$\dot{x}(t) = f(x(t), u(t), t) \quad (6)$$

The problem is stated as the minimization of the integral form of L [33,34];

$$J = \int_{t_0}^{t_f} L(x(t), u(t), t) dt + M(x(t_f), t_f) \quad (7)$$

The objective is to find the optimal control trajectory $u(t)$ that minimizes the cost function J . M is the terminal cost. In practice, we add the system dynamics to L by introducing a vector of cost variables λ , avoiding the integral form:

$$H(x, u, \lambda, t) = L(x, u, t) + \lambda^T f(x, u, t) \quad (8)$$

Pontryagin's Minimum Principle (PMP) states that, for an optimal trajectory $x^*(t), u^*(t)$, the Hamiltonian is minimized [35,36]:

$$H(x^*(t), u^*(t), \lambda^*(t), t) = \min_u H(x^*(t), u, \lambda^*(t), t) \quad (9)$$

$\lambda(t)$ is the adjoint vector, satisfying the adjoint differential equation:

$$\dot{\lambda}(t) = -\frac{\delta H}{\delta x} \quad (10)$$

3.2. PMP Applied to the Energy Management Problem

The main objective of the ECMS is to find a local minimum for equivalent fuel consumption while also satisfying constraints. These constraints are imposed by the driver's power demand, the EM limitations, and the battery power and capacity limitations.

$$J_t = J_t(P_{ICE}(t), P_{EM}(t)) \quad (11)$$

$$\{P_{ICE}^{opt}(t), P_{EM}^{opt}(t)\} = \arg \min_{\{P_{ICE}(t), P_{EM}(t)\}} J_t \quad (12)$$

$$\begin{cases} P_{req}(t) = P_{ICE}(t) + P_{EM}(t) \\ SOC_{min} < SOC(t) < SOC_{max} \quad \forall t \\ 0 \leq P_{ICE}(t) \leq P_{ICE\ max}(t) \\ P_{EM\ min}(t) \leq P_{EM}(t) \leq P_{EM\ max}(t) \end{cases} \quad (13)$$

where J_t is the total consumption, P_{ICE} is the ICE power, P_{EM} is the EM power, and P_{req} is the required power determined by the driver. Equation (13) shows the constraints imposed on the battery, ICE and EM. Consumption of fuel and equivalent consumption of electrical energy can be defined as:

$$J_t = \dot{m}_{ICE}(P_{ICE}(t)) + s(t) \cdot \dot{m}_{EM\ eq}(P_{EM}(t)) \quad (14)$$

where $\dot{m}_{ICE}$ is the fuel consumption and $\dot{m}_{EM\ eq}$ is the equivalent fuel consumption that depends on the EM. The equivalent factor or penalty factor $s(t)$ is a function of the SOC, and it increases or reduces the use of the electric motor in order to keep the battery SOC within its limits. In order to approach the optimal solution using the ECMS, the penal factor should be chosen carefully. Practically, a large $s(t)$ value penalizes the use of electrical energy, which increases engine fuel consumption, while a small $s(t)$ value eliminates the penalty, resulting in more electrical energy use. Assigning the penalty factor to a fixed value is insufficient fuel economy, since the changes in the driving cycles, the current SOC value, and the charge and discharge situation affect the optimum value of $s(t)$.

Mathematically, the term s is expressed using different formulations, with different results on the ECMS controller:

$$s = s_{opt} + \tan(SOC_{ref} - SOC(t))K_s s_{opt} \quad (15)$$

$$s = K_p (SOC_{ref} - SOC(t)) + K_i \int (SOC_{ref} - SOC(t)) dt \quad (16)$$

In Equation (10), the equivalent factor s is calculated using the tangent function and the optimal equivalent factor s_{opt} . The optimal equivalent factor is calculated offline for minimizing the fuel consumption over a specific driving cycle. On the other hand, Equation (16) uses the PI approach, with proportional and integral gains, K_p and K_i . These methods have the drawback that they do not maintain the actual $SOC(t)$ inside the specified boundaries. Another problem is the selection of the optimal equivalent factor s_{opt} , which

is strongly dependent on the type of driving cycle [37]. In this study penalty function is defined as follows:

$$s(t) = f_{SOC}(s(t)) \cdot s_k \quad (17)$$

$$f_{SOC}(s(t)) = \left(1 + \left(\frac{SOC_{ref} - SOC(t)}{SOC_{ref} - SOC_{min}} \right)^{2n_{SOC}+1} \right) \cdot \left(1 + \tanh \left(\frac{f_{SOC,I}(SOC(t))}{SOC_{th}} \right) \right) \quad (18)$$

$f_{SOC,I}$ is:

$$f_{SOC,I}(SOC(t)) = 0.99 \cdot f_{SOC,I}(t - \Delta t) + 0.01 \cdot (SOC_{ref} - SOC(t)) \quad (19)$$

where SOC_{min} and SOC_{max} values depend on the battery type. The aggressiveness of the controller can be adjusted by setting the value of n_{SOC} .

As illustrated in Figure 8, increasing the n_{SOC} value leads to a steeper penalty gradient, which results in more aggressive energy recuperation behavior during low battery levels. The solid black line in Figure 8a and the dashed line in Figure 8b indicate the specific n_{SOC} value used in this study for controller tuning and simulation analysis. The color shading in Figure 8b represents the magnitude of the penalty factor s . The value of n_{SOC} must be selected such that the drive cycle constraint is fulfilled. Numerical methods are available in the literature [38–43]. In addition, with some optimization techniques, the n_{SOC} value of the controller, especially with a constant driving cycle, can be calculated to minimize energy consumption.

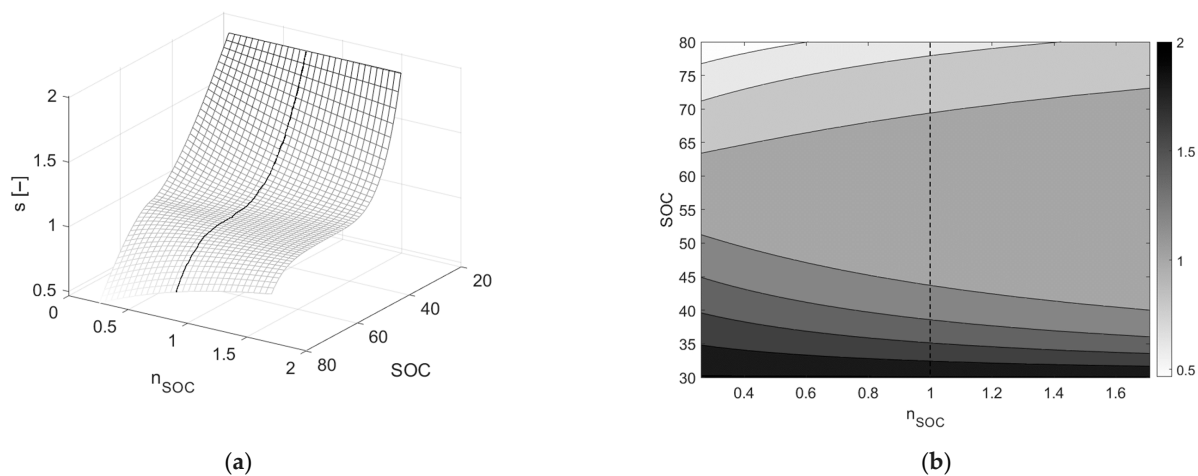


Figure 8. (a) 3D surface plot showing the relationship between s , n_{SOC} , and SOC (b) Contour map of the Aggressiveness factor.

4. Simulation Results

For the simulation purposes, NREL, FTP-SC03, FIGE, and Orange drive cycles are considered. Although both real-world and standardized drive cycles were used in this study, a direct comparative analysis was not performed due to the inherent differences in their structure. Future work will include normalized performance comparisons and a VSP-based analysis to identify the operational conditions under which ECMS yields the most benefit. It is noted that many scenarios have been made due to the different energy management algorithm, which used an ECMS and conventional rule-based control.

Depending on whether the SHEV is (TM) or (GVM), range results were obtained from four driving cycles, with weights of 6800 kg and 13,800 kg, respectively. For comparison, the simulation was repeated under the same conditions using the classical rule-based controller. These driving cycles were chosen because they are designed for semi-commercial vehicles.

To check the performance of the algorithm, the battery operating regions are also analyzed. Figure 9 shows that the developed algorithm successfully keeps the SOC in the predefined limits. Additionally, torque applied to the EM that is working in the generator is shown in Figure 7. As expected, when the SOC hits the lower limit, ICE starts to operate to apply a torque to the input of the EM to generate electricity, thus charging the battery.

Figure 9 shows the SOC and ICE torque for the ECMS algorithm. In the NREL driving cycle, there is a 13.5% increase in the range for GVM. Additionally, in the FTP-SC03, FIGE, Orange, and WLTP cycles, there is a 14%, 13.23%, 12.8%, and 11.9% increase in the range, respectively. Although the increase in range is approximately the same for each driving cycle, the same rate of change was not observed for emission, since the tailpipe emission highly depends on the ICE's operating point. However, there is still a significant reduction in the emission for the FTP-SC03 driving cycle. Table 2 represents the comparison of ECMS and rule-based controllers for the range across five drive cycles, and Table 3 represents comparison of the exhaust emission data (CO, NO_x, CO₂) under both control strategies.

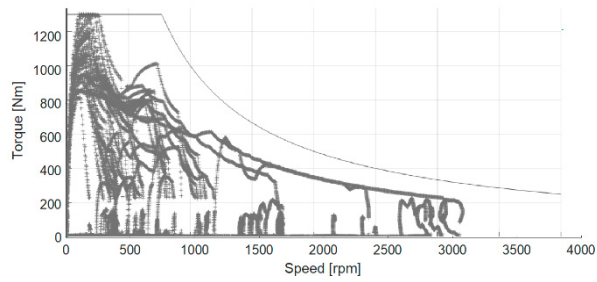
Table 2. Comparison of ECMS and rule-based controller for range.

	ECMS	Rule-Based Controller	
		Range (km)	%
NREL	190.3	167.37	13.5
FTP SC03	306.6	268.78	14
FIGE	305.1	269.44	13.23
Orange	218.6	193.70	12.8
WLTP	260.5	232.7	11.9

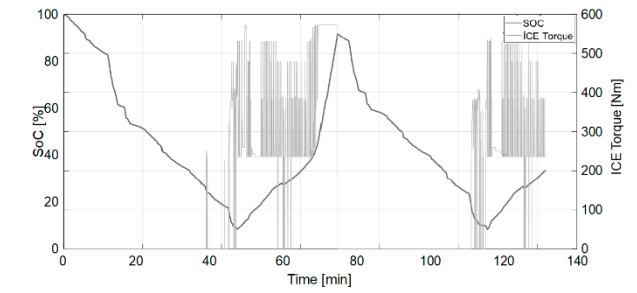
Table 3. Emission results of the ECMS controller.

	ECMS/Rule-Based		
	CO (g/km)	NO _x (g/km)	CO ₂ (g/t-km)
NREL	1.91/2.01	3.97/4.05	86.13/92.7
FTP SC03	1.61/2.74	6.07/7.89	89.54/91.3
FIGE	1.34/1.61	6.29/7.86	93.47/101.2
Orange	1.81/2.72	3.7/5.66	80.57/83.3
WLTP	1.14/1.54	3.0/4.14	57.26/79.1

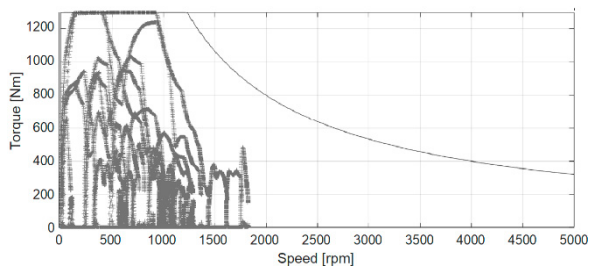
Results have demonstrated that the range of the vehicle increased based on the velocity profile. In the NREL drive cycle, the vehicle range increased 13.5% with respect to the rule-based controller. The highest range increase is achieved in the FTP-SC03 with 14%, whereas the lowest range increase is obtained in the WLTP cycle, with an 11.9% increase in the range, respectively. Although the increase rate in the range is approximately the same for each driving cycle, the same rate of change was not observed for the emission, since the tailpipe emission highly depends on the ICE's operating point. Table 2 presents the comparison of ECMS and rule-based controllers in terms of the range.



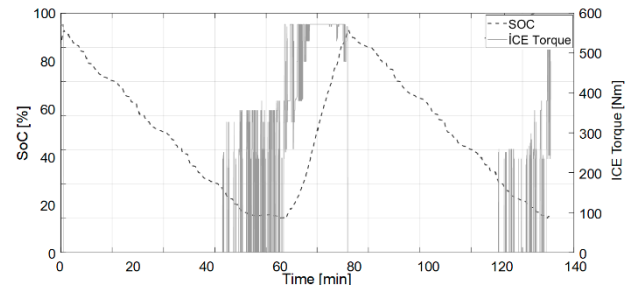
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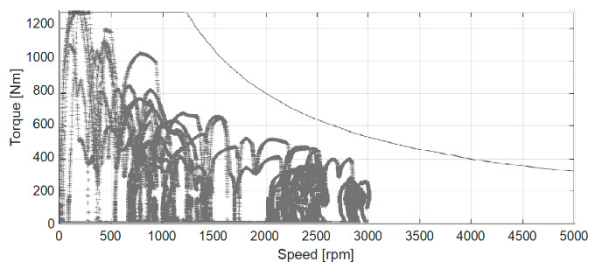
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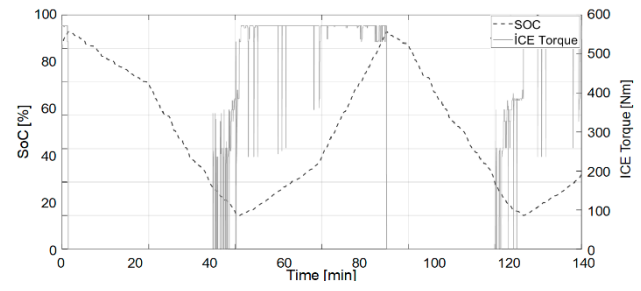
(c)



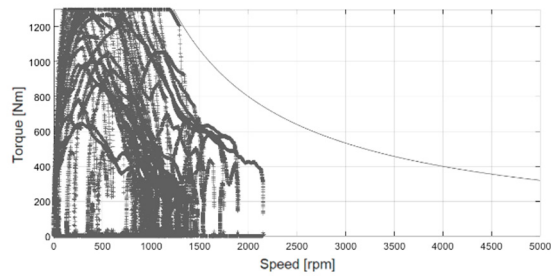
(d)



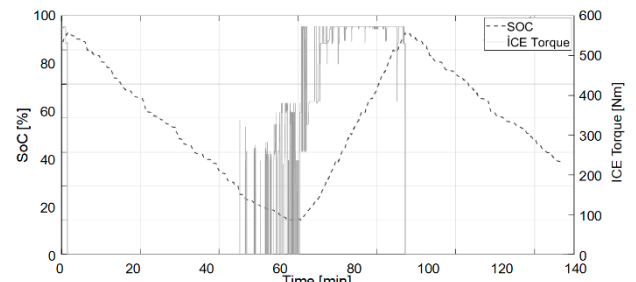
(e)



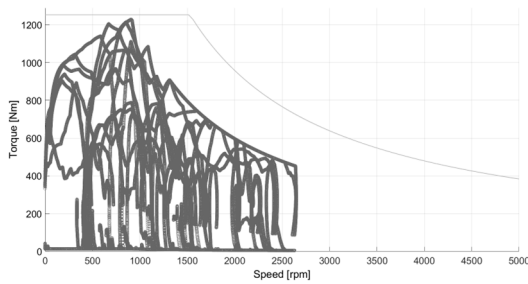
(f)



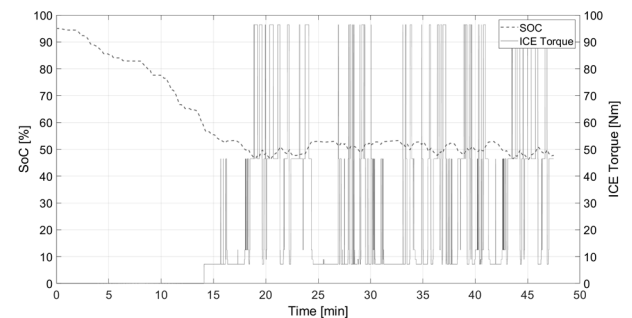
(g)



(h)



(i)



(j)

Figure 9. Shows all drive cycles and operating points of EM and (a,b) NREL, (c,d) FTP-SC03, (e,f) FIGE, (g,h) Orange cycle, and (i,j) WLTP cycle EM operation point and SOC, respectively.

5. Conclusions and Discussion

In this paper, innovative ECMS facilitates the optimized operation of the powertrain components in a hybrid electric vehicle (HEV), consisting of the internal combustion engine (ICE), electric motor (EM), and battery. The intelligent management of these components is achieved by predicting the HEV's future power requirements and utilizing the most efficient approach to meet them. With the ECMS, the HEV's powertrain components are operated more efficiently, resulting in improved performance and reduced energy consumption. The ECMS currently under consideration offers two essential functionalities.

Prior to final deployment, the ECMS controller was tested using a dSPACE real-time prototyping platform with a virtual vehicle model, enabling hardware-in-the-loop (HIL) validation. This confirmed the controller's operational performance under varying load and driving conditions and provided an intermediate step between simulation and real-world implementation.

Refuse trucks represent a unique application for series hybrid systems due to their operational patterns, which involve frequent stopping and idling. Hybrid refuse trucks can achieve significant reductions in fuel consumption and emissions compared to conventional trucks. By implementing ECMS, these benefits can be further enhanced. The ECMS can effectively manage the energy flow in hybrid refuse trucks, optimizing fuel efficiency and reducing emissions during stop-and-go operations.

Firstly, it efficiently manages the state of charge of the battery, which is imperative to extend its lifespan and ensure that sufficient power is available to meet the peak energy demands of the vehicle. Secondly, it has the capacity to enhance the fuel efficiency of the vehicle and reduce its carbon footprint by optimizing the operation of the ICE and minimizing its runtime. By virtue of these two functionalities, the ECMS plays a pivotal role in enhancing the overall performance of the vehicle while simultaneously ensuring its sustainability.

The efficacy of the proposed ECMS was evaluated through simulation using five different driving cycles, namely, NREL, FTP-SC03, FIGE, and OCB and WLTP. The outcomes reveal that the suggested ECMS has the potential to enhance the range of Hybrid Electric Vehicles (HEVs) in all four driving cycles. The most significant range improvement was observed in the FTP-SC03 driving cycle with a 14% increase in range. Conversely, the WLTP driving cycle showed the lowest range enhancement, with an 11.9% increase in range.

The emission results comparing the Equivalent Energy Consumption Minimization Strategy (ECMS) controller to the rule-based controller across various driving cycles reveal significant improvements with the ECMS implementation. In the NREL driving cycle, the ECMS reduced carbon monoxide (CO) emissions from 2.01 g/km to 1.91 g/km, and nitrogen oxides (NO_x) emissions from 4.05 g/km to 3.97 g/km. Similarly, CO₂ emissions were lowered from 92.7 g/t-km to 86.13 g/t-km. These reductions indicate that the ECMS is more effective in controlling emissions during this cycle. The FTP SC03 cycle showed even more substantial benefits. The ECMS reduced CO emissions from 2.74 g/km to 1.61 g/km, and NO_x emissions from 7.89 g/km to 6.07 g/km. CO₂ emissions also decreased from 91.3 g/t-km to 89.54 g/t-km. This cycle highlights the ECMS's ability to manage emissions under more stringent conditions effectively.

In the FIGE cycle, the ECMS further demonstrated its efficiency by lowering CO emissions from 1.61 g/km to 1.34 g/km and NO_x emissions from 7.86 g/km to 6.29 g/km. CO₂ emissions saw a notable reduction from 101.2 g/t-km to 93.47 g/t-km, showing the system's robustness in varying driving conditions.

The Orange cycle results also supported the ECMS's superiority, with CO emissions reduced from 2.72 g/km to 1.81 g/km and NO_x emissions from 5.66 g/km to 3.7 g/km.

CO₂ emissions were reduced from 83.3 g/t-km to 80.57 g/t-km, reinforcing the pattern of improved emissions control.

Finally, the WLTP cycle, known for its comprehensive assessment of vehicle emissions, showed significant reductions in all measured pollutants. The ECMS reduced CO emissions from 1.54 g/km to 1.14 g/km, NO_x emissions from 4.14 g/km to 3.0 g/km, and CO₂ emissions from 79.1 g/t-km to 57.26 g/t-km. This cycle's results underscore the ECMS's capability to deliver substantial environmental benefits [44–46].

In order to advance the development of the proposed ECMS, it is imperative to consider prospective endeavors. This may entail evaluating the ECMS on a genuine HEV test vehicle, creating a more sophisticated battery model that can enhance the accuracy of the ECMS's predictions, and developing a more resilient ECMS algorithm that is less susceptible to changes in the vehicle's operational environment. These future efforts hold the potential to fortify the ECMS's performance and optimize its functionality.

ECMS for a hybrid electric vehicle is proposed and its performance is assessed through different drive cycles which are NREL, FTP-SC03, FIGE, and OCB and WLTP. First, a forward-facing simulation model is developed in order to integrate the developed control strategy [47,48]. Afterwards, models of the e-powertrain are built and brought together in MATLAB® R2023a (The MathWorks, Inc., Natick, MA, USA). Calculation of the total equivalent fuel consumption and determining minimum consumption were analyzed from different perspectives to select the correct penalty factor between the fuel and the electrical energy. Simulation results have shown that proposed ECMS can provide significant improvements in the range. To assess the performance of the developed algorithm, a rule-based control strategy is built. It is mainly selected due to its simple structure. Results have demonstrated that the range of the vehicle can be increased using ECMS in the range of 11.09% up to 14%, based on the drive cycle and characteristics of the electric powertrain components in comparison to the rule-based control strategy.

While standardized drive cycles were used for general benchmarking, initial validation of the ECMS was performed using real-world measurements. Future studies will focus on systematic comparison between real and standardized cycles, potentially through Vehicle Specific Power (VSP) distribution analysis, to quantify the performance variation.

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Abbreviations

ECMS	Equivalent Energy Consumption Minimization
HEV	Hybrid Electric Vehicle
SHEV	Series Hybrid Vehicle
TM	Tare Mass
GVM	Gross Vehicle Mass
PHEV	Parallel Hybrid Vehicle
PMP	Pontryagin's Minimum Principle
ICE	Internal Combustion Engine
EG	Electric Generator
BP	Battery pack
SOC	State of Charge
BLDC	Brushless Direct Current Motor
OCV	Open Circuit Voltage
OCB	Orange Country Bus
WLTP	Worldwide Harmonized Light-Duty Vehicles Test Procedure
NREL	National Renewable Energy Laboratory
GENSET	Generator Set
PDU	Power Distribution Unit

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