Department of Electrical and Computer Engineering

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Power Management Control of a Series Plug-In Hybrid Electric Vehicle Using Rule-Based Control, Dynamic Programming Benchmark, and QSS-Toolbox Simulation

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Abstract

This report covers the design, simulation, and benchmarking of a rule-based power management controller for a series plug-in hybrid electric vehicle (PHEV), implemented in the QSS-Toolbox for MATLAB/Simulink. The controller monitors battery state of charge (SOC) and engages the internal combustion engine (ICE) via an SR latch when charge falls below 90% of the initial value. The powertrain model encompasses all major subsystems: driving cycle, vehicle dynamics, manual gearbox, electric motor, battery, a custom battery controller with generator ramp logic, simple transmission, combustion engine, electric generator, and fuel tank.

Validation was performed across four standard drive cycles (NEDC, EUDC, FTP-75, FTP-Highway) starting at 45% SOC. Fuel consumption ranged from 0.126 L eq./100km on FTP-Highway to 2.636 L eq./100km on FTP-75, representing reductions of 71% to approximately 98% against a conventional ICE baseline. On the NEDC, the engine operated for only 10.8% of the cycle, yielding 1.770 L/100km against a 7.0 L/100km baseline. An independent forward-dynamic validation model confirmed the qualitative behaviour, with a 43% deviation consistent with known QSS optimism under generator ramp and SR latch dynamics.

A dynamic programming (DP) benchmark on the same QSS model establishes a cycle-optimal lower bound of 1.285 L/100km on the NEDC. The rule-based controller at 1.770 L/100km sits 37.8% above the DP optimum, within the 10–40% range reported in the literature for thermostatic strategies, and quantifies the specific improvement available from advancing to adaptive or optimization-based control.

Table of Contents

1. Introduction

Fuel economy and emissions have pushed the auto industry toward electrification faster than most people expected. Among the available options, plug-in hybrid electric vehicles (PHEVs) sit in a useful middle ground: they can run on battery alone for short trips, fall back on the ICE for longer ones, and get recharged from the grid like a full EV. The result is a large drop in fuel use, particularly in urban driving where the engine barely needs to run at all.

In a series PHEV, the ICE never directly drives the wheels. The motor handles all traction, and the engine only runs when it needs to top up the battery through a generator. That separation means the engine can always run at its most efficient operating point regardless of the instantaneous road load, which is a fundamental advantage over conventional parallel or series-parallel powertrains. The controller that decides when to turn the engine on and off is essentially what determines how much fuel gets used.

PHEVs typically operate in two distinct modes depending on battery state. In charge-depleting (CD) mode, the vehicle draws primarily from the battery and minimises engine use, allowing SOC to fall over time. Once SOC falls to a defined threshold, the vehicle transitions to charge-sustaining (CS) mode, in which the engine runs periodically to keep the battery within a target band. The rule-based controller in this project implements exactly this logic: it monitors SOC and fires the engine via an SR latch when charge drops below 90% of the initial value.

This project builds and tests a rule-based power management controller for a series PHEV using the Quasistatic Simulation (QSS) Toolbox from ETH Zurich [1] in MATLAB/Simulink. A key addition beyond a standard rule-based study is a quasi-static dynamic programming (DP) benchmark computed on the same QSS model. DP gives the globally optimal fuel consumption for the known drive cycle and serves as a hard lower bound, allowing the actual cost of the fixed-threshold strategy to be measured precisely rather than relying on generic literature ranges.

Section 2 surveys PHEV power management approaches in the literature. Section 3 describes the powertrain model block by block. Section 4 covers controller design and MATLAB code. Section 5 presents the DP benchmark and its derivation. Section 6 presents and discusses simulation results across all four drive cycles. Section 7 concludes with quantified findings and future directions.

2. Literature Survey

PHEV power management has been studied for over twenty years. The core problem is always the same: given some demanded power, how do you split it between the engine and motor in real time to burn as little fuel as possible without violating battery limits or making the vehicle feel rough to drive? The answer depends heavily on how much computation the controller can do in real time and how much information about the future trip it has access to.

2.1 Sensors and Actuators

The most important input for a PHEV controller is battery SOC, which cannot be measured directly. In real systems it gets estimated from voltage, current, and temperature using techniques like coulomb counting, open-circuit voltage (OCV) lookup, or extended Kalman filters [2]. Coulomb counting is simple but accumulates error over time; OCV-based estimation is accurate at rest but unavailable during dynamic operation; Kalman filter approaches combine both and can track SOC to within 1–2% in practice [2], but require a validated battery model. In the QSS model used here, the battery block integrates the power balance directly, so the SOC signal is exact. On the input side beyond SOC, vehicle speed is measured by a wheel speed sensor or derived from the driving cycle signal, engine speed comes from a crankshaft position sensor, and battery current and terminal voltage are sampled by dedicated measurement circuits. Battery temperature is monitored by NTC thermistors mounted on the cell pack; this reading feeds into the SOC estimator to compensate for the temperature-dependence of internal resistance and open-circuit voltage [2]. On the output side, the battery controller sends three command signals, w_cntl, dw_cntl, and T_cntl, that set the generator reference speed, speed ramp rate, and torque reference respectively. In a production system these commands would be passed to a dedicated engine control unit (ECU) and an inverter gate-driver board; in the QSS model they connect directly to the Geno-Group On block. The throttle actuator on the combustion engine and the power electronics switching the motor inverter are the primary output actuators; their response dynamics are abstracted away in the quasistatic framework but become important in the forward-dynamic validation discussed in Section 6.6.

2.2 Rule-Based Control

Rule-based controllers are the most common approach in production vehicles because they are simple, run in real time, and are straightforward to tune and certify for automotive safety standards. The simplest form is thermostatic on/off control: engine on when SOC falls below a threshold, engine off when it recovers [3]. Lin et al. [3] demonstrated this on a parallel hybrid truck and showed that careful threshold selection, rather than algorithmic sophistication, accounts for most of the achievable fuel savings.

More advanced heuristic approaches such as power-follower control adjust the engine set point dynamically based on current power demand rather than SOC alone, smoothing out switching transients. Fuzzy logic controllers replace the hard SOC threshold with overlapping membership functions that produce smooth CD-to-CS transitions. Sciarretta and Guzzella [6] compared thermostatic, power-follower, and fuzzy logic strategies and found fuzzy logic reduced fuel consumption by an additional 4–8% under varied real-world driving patterns, at the cost of additional calibration effort. Pisu and Rizzoni [4] showed that well-tuned thermostatic controllers typically land within 10–20% of the DP optimum under standard drive cycles, which is the benchmark used to evaluate this project in Section 6.

2.3 Optimization-Based Approaches

Dynamic programming (DP) gives the globally optimal solution for a known drive cycle by solving Bellman's equation backwards through the time horizon [5, 11, 12]. DP cannot run online since it requires the full trip in advance, but it serves as an offline benchmark: by computing the DP-optimal fuel

consumption on the same powertrain model, one can quantify precisely how much the chosen real-time strategy leaves on the table. That is the role DP plays in Section 5 of this report.

Equivalent Consumption Minimisation Strategy (ECMS) and Pontryagin's minimum principle translate the DP optimality condition into a real-time form by introducing an equivalence factor that converts electrical energy into an equivalent fuel cost [6]. Musardo et al. [5] showed that Adaptive ECMS (A-ECMS) closes most of the gap between fixed-equivalence ECMS and DP. Model predictive control (MPC) uses a short-horizon speed prediction to optimise the power split over the next N steps [7]. On the model-free side, extremum seeking (ES) control, used by Prof. Chen's group at the University of Windsor for diesel engine fuel injection optimisation [8], tunes itself without a plant model, making it a natural next step beyond the fixed-threshold strategy used here.

2.4 Quasi-Static vs. Forward-Dynamic Simulation

In the forward-dynamic approach, a driver model applies throttle or brake commands and the resulting speed is computed by integrating Newton's second law. The quasi-static (QSS) approach inverts this: the drive cycle speed profile is treated as a known input and power flows are computed backwards from wheels to engine at each timestep [1]:

$$\Sigma F = m \cdot a + \tfrac{1}{2} \cdot \rho \cdot C\_D \cdot A\_f \cdot v^2 + m \cdot g \cdot c\_r \quad (0)$$

No driver model is needed and each timestep is independent, making QSS far faster while capturing average fuel consumption accurately. Guzzella and Sciarretta [1] show QSS is appropriate for control strategy development and fuel economy benchmarking. Forward-dynamic simulation captures inertial lag and controller hysteresis, making it more suitable for validation. The 43% deviation in Section 6.6 is consistent with published QSS-vs-forward comparisons, where 20–50% optimism is typical when ramp dynamics and latch hysteresis are included [1, 10].

3. Powertrain Model

The powertrain is built in MATLAB/Simulink using the QSS-Toolbox from ETH Zurich [9]. In this series hybrid layout, the motor handles all traction and the engine only runs to charge the battery through the generator when SOC drops below the threshold. Figure 1 shows the complete model. All numerical parameters are consolidated in Table 1.

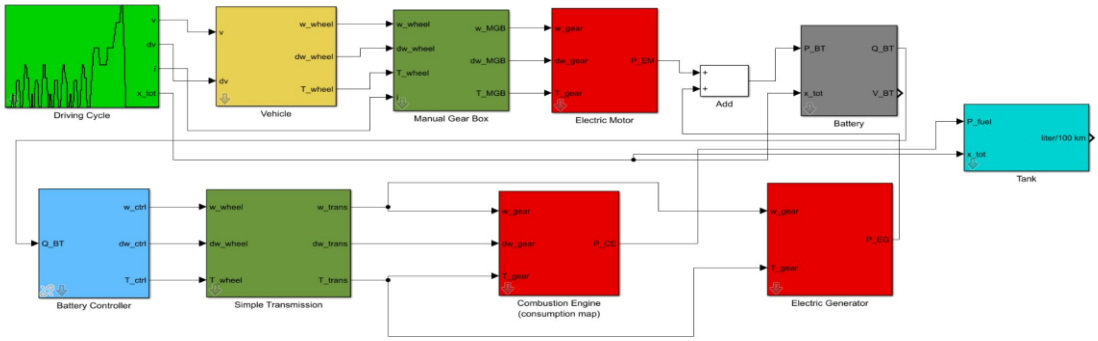

Figure 1. Complete series PHEV powertrain model in MATLAB/Simulink (QSS-Toolbox).

3.1 Driving Cycle Block

The driving cycle block feeds the model with vehicle speed v [m/s], acceleration dv [m/s²], gear number i, and total distance x_tot [m] at 1-second steps. Europe: NEDC is selected as the default drive cycle, with automatic stop enabled. The NEDC runs for approximately 1180 seconds: four repeated ECE-15 urban segments (0–780 s) up to 50 km/h, followed by a single EUDC highway segment (780–1180 s) reaching 120 km/h. Block parameters are shown in Figure 2.

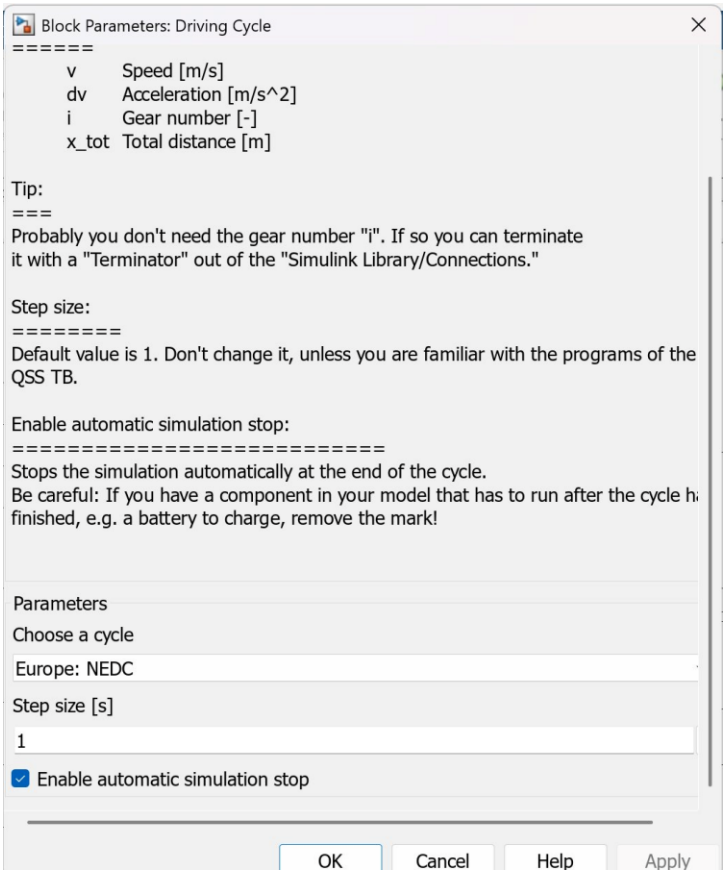

Figure 2. Block parameters for the Driving Cycle block (Europe: NEDC, step size = 1 s).

3.2 Vehicle Block

From speed and acceleration inputs, the vehicle block computes wheel torque T_wheel, angular speed ω_wheel, and angular acceleration dω_wheel. The total tractive force is the sum of three components:

$$F_{aer} = \tfrac{1}{2}\cdot\rho\cdot C_D\cdot A_f\cdot v^2 \quad (1)$$

$$F_{rr} = m\cdot g\cdot c_r \quad (2)$$

$$F_{in} = m_{eq}\cdot(dv/dt) \quad (3)$$

$$F_{tract} = F_{aer} + F_{rr} + F_{in} \quad (4)$$

where $m_{eq} = m(1 + 4\cdot J_{wheel}/r^2)$ accounts for the four rotating wheel inertias. Block parameters and all numerical values are given in Figure 3 and Table 1.

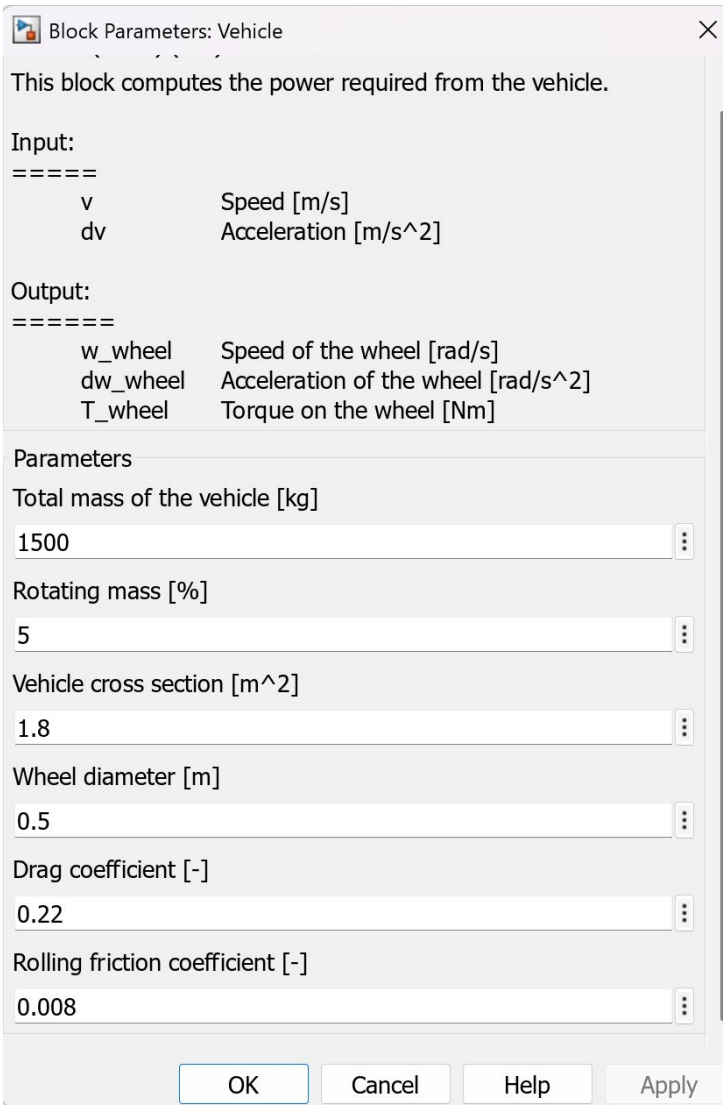

Figure 3. Block parameters for the Vehicle block.

Table 1. Vehicle and powertrain simulation parameters.

Parameter	Value	Unit
Total vehicle mass	1500	kg
Vehicle cross section (A_f)	1.8	m²
Drag coefficient (C_D)	0.22	—
Rolling friction coefficient (c_r)	0.008	—
Wheel diameter	0.5	m
Rotating mass	5	%
Battery capacity	141	Ah
Battery OCV (fully charged)	130	V
Initial SOC	45	%

Parameter	Value	Unit
Engine type	Otto (gasoline)	—
Engine displacement	1.6	L
Engine idle speed	105	rad/s
Engine idle power	2600	W
Auxiliary power	300	W
Engine fuel cutoff torque	5	Nm
Generator scaling factor	6	—
Motor scaling factor	5	—
Motor inertia	0.5	kg·m²

3.3 Manual Gearbox Block

The manual gearbox converts wheel-side speed, acceleration, and torque to the motor shaft using the gear number from the driving cycle block. Default QSS-Toolbox gear ratios are used: 9, 7, 5, 4, 3 for gears 1 through 5. Differential ratio is 1, efficiency is 0.98, and idling friction losses are 300 W.

3.4 Electric Motor Block

The motor block uses an efficiency map to convert shaft speed and torque demand into electrical power P_EM. Scaling factor is 5, rotor inertia is 0.5 kg·m², and auxiliary power is 0 W. Block parameters are shown in Figure 4.

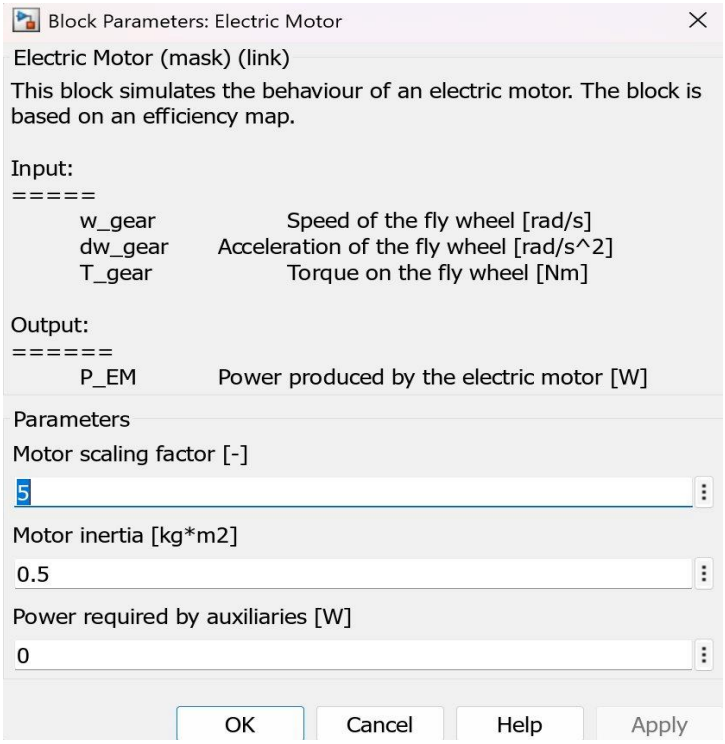

Figure 4. Block parameters for the Electric Motor block.

3.5 Battery Block

The battery block models a 141 Ah lead-acid battery with an open-circuit voltage of 130 V at full charge. Initial SOC is 45% and the minimum charge/discharge time is 20 minutes. The SOC update at each timestep is:

$$Q\_BT(k+1) = Q\_BT(k) - P\_BT(k) \cdot h \,/\, V\_OC \quad (5)$$

where h = 1 s is the timestep and P_BT is positive during battery discharge. Block parameters are shown in Figure 5.

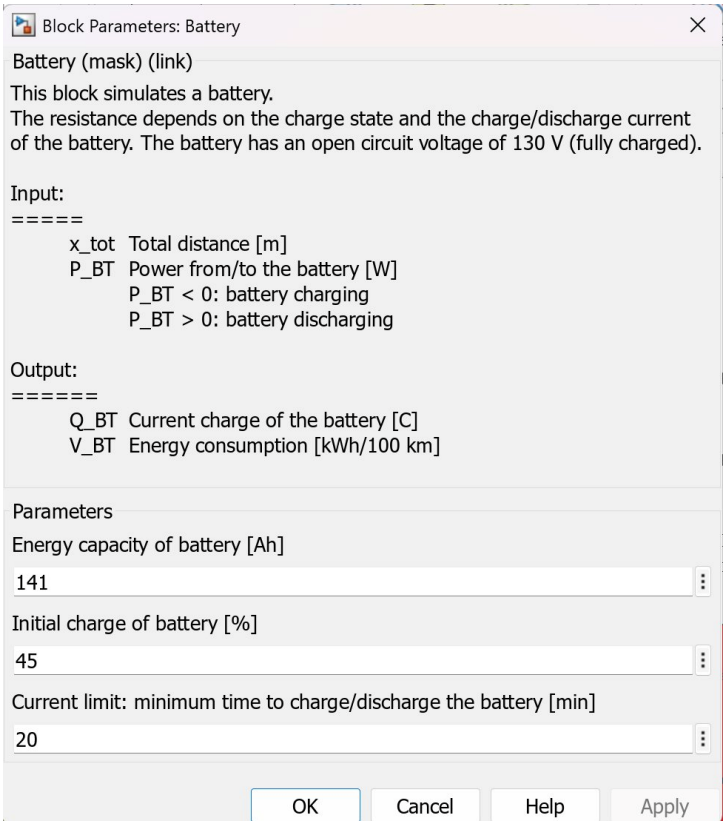

Figure 5. Block parameters for the Battery block (141 Ah, initial SOC = 45%, current limit = 20 min).

3.6 Battery Controller Block

The battery controller is a custom subsystem, not the standard QSS-Toolbox one. It compares Q_BT against Q_BT_min, uses an SR latch to produce the cc_on flag, and passes it to the Geno-Group On block which manages the generator ramp. Figures 6, 7, and 8 show the top-level structure, the Geno-Group On internals, and the counter sub-block respectively.

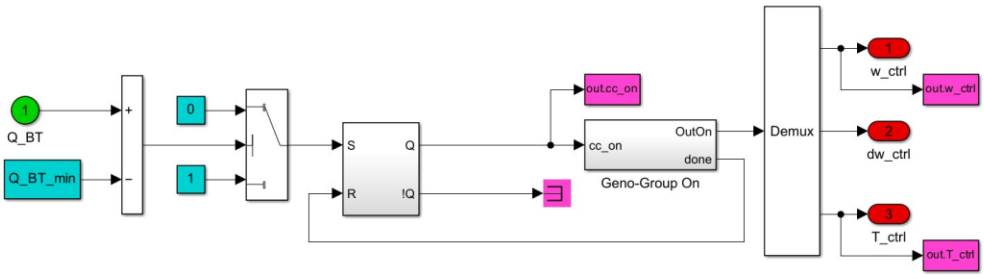

Figure 6. Battery Controller block internal structure (top level).

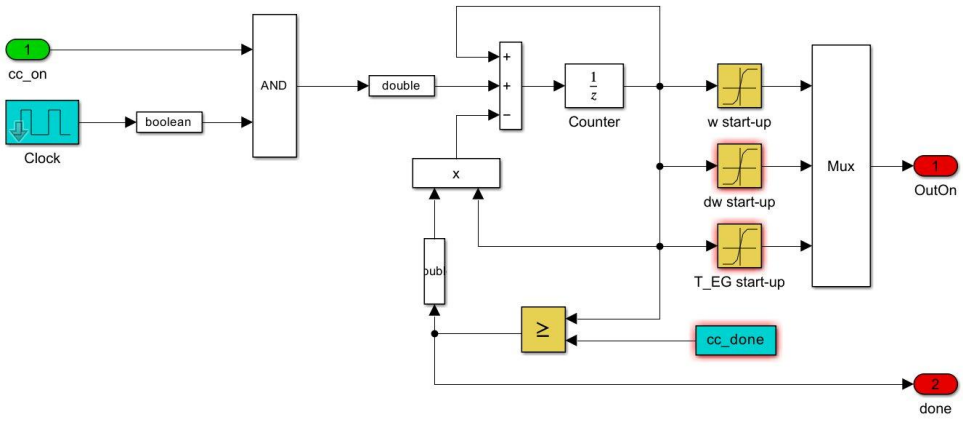

Figure 7. Geno-Group On block internals, showing generation of w_ctrl, dw_ctrl, T_ctrl ramp signals.

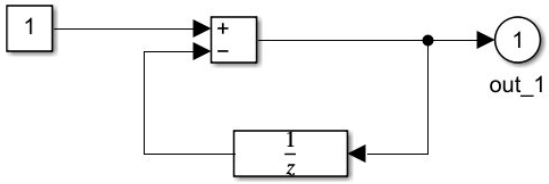

Figure 8. Counter sub-block internals.

3.7 Simple Transmission Block

The CE-EG transmission block sits between the battery controller and the engine/generator pair. Fixed gear ratio is 1 (direct drive), efficiency is 0.98 with 200 W of idling losses. Block parameters are shown in Figure 9.

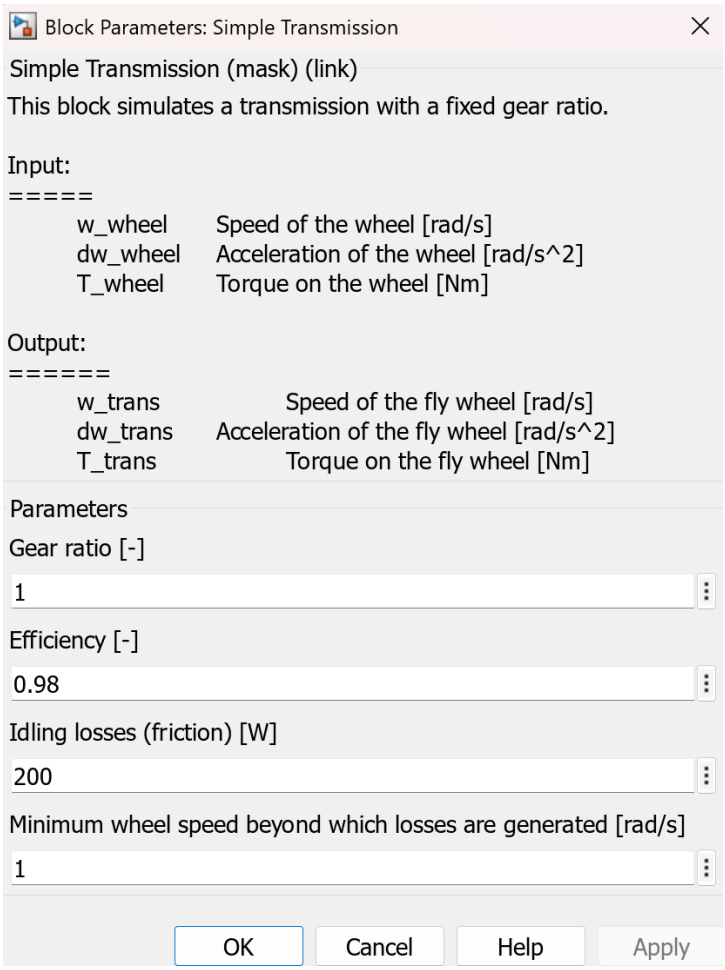

Figure 9. Block parameters for the Simple Transmission block (gear ratio = 1, efficiency = 0.98, idling losses = 200 W).

3.8 Combustion Engine Block

The combustion engine block looks up fuel consumption from a 2D map indexed by torque and speed, outputting the fuel rate and mechanical power P_CE. Configured as an Otto-cycle engine with 1.6 L displacement, idle speed 105 rad/s, idle power 2600 W, auxiliary load 300 W, and fuel cutoff enabled below 5 Nm. Block parameters are shown in Figure 10.

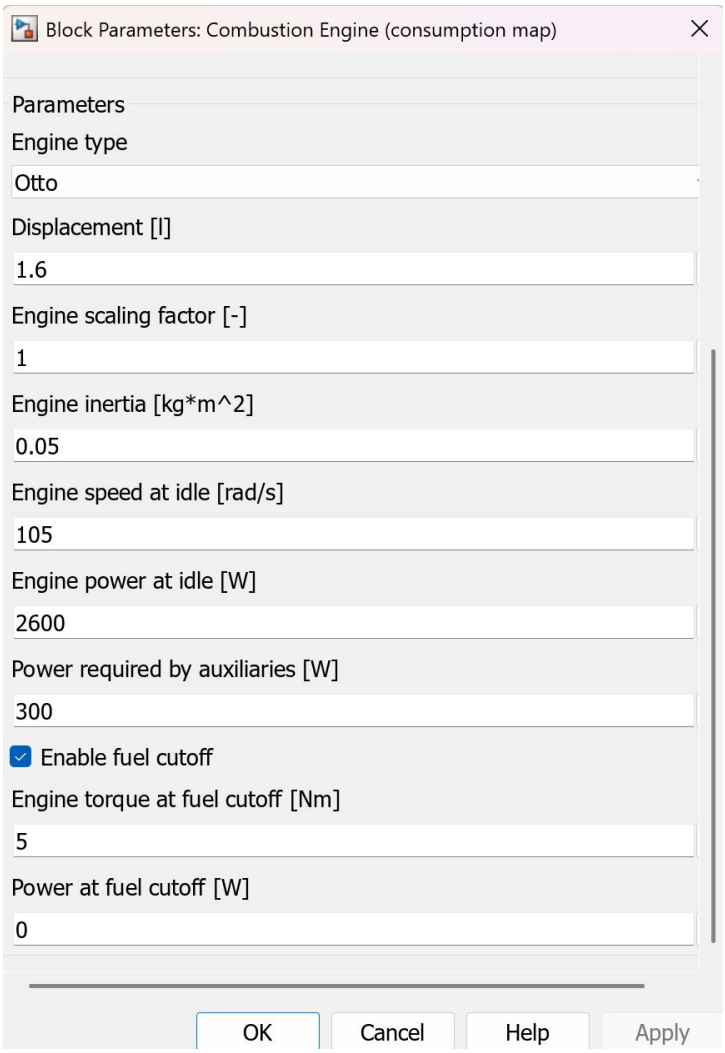

Figure 10. Block parameters for the Combustion Engine block.

3.9 Electric Generator Block

The generator block takes speed and torque from the CE-EG transmission and uses an efficiency map to compute the electrical output P_EG. Scaling factor is 6. Block parameters are shown in Figure 11.

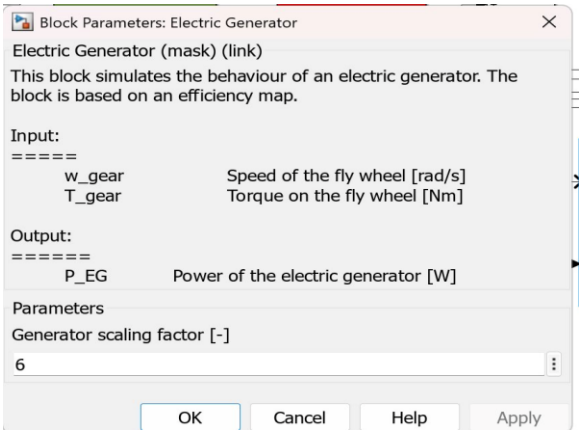

Figure 11. Block parameters for the Electric Generator block (scaling factor = 6).

3.10 Power Summation and Fuel Tank

A simple Add block combines the three power signals according to the series PHEV power balance, where P_EG and P_CE carry negative values when the generator is charging the battery:

$$P\_BT = P\_EM + P\_EG + P\_CE \quad (6)$$

P_EM draws from the battery; P_EG and P_CE are negative when the generator is charging. The tank block integrates fuel consumption from P_CE over total distance x_tot:

$$V\_fuel = \int P\_CE\, dt \,/\, (H\_f \cdot \rho\_f \cdot x\_tot/100) \quad (7)$$

where H_f = 43.2 MJ/kg and ρ_f = 0.74 kg/L.

4. Controller Design

4.1 Rule-Based Strategy

The controller uses a thermostatic on/off strategy. It watches Q_BT continuously and compares it to Q_BT_min, set at 90% of the initial charge Q_BT_IC. When Q_BT dips below that threshold, the SR latch sets cc_on = 1 and Geno-Group On starts ramping the generator speed from zero toward 480 rad/s. Once Q_BT recovers, cc_on returns to 0 and the generator ramps back down. The switching logic and speed ramp are:

$$Q\_BT\_min = 0.90 \cdot Q\_BT\_IC \quad (8)$$

$$cc\_on = 1 \text{ if } Q\_BT < Q\_BT\_min; \quad cc\_on = 0 \text{ if } Q\_BT \geq Q\_BT\_min \quad (9)$$

$$\omega\_gen(k+1) = clamp(\omega\_gen(k) \pm 5,\ 0,\ 480)\ [\text{rad/s per second}] \quad (10)$$

At +5 rad/s per step, the generator takes 96 seconds to reach full speed, keeping torque changes smooth, which matters in the quasistatic framework where sudden power jumps are not physically realistic. All controller parameters are in Table 2.

Table 2. Rule-based controller parameters.

Parameter	Value	Description
Q_BT_min (q_minimum)	90% of Q_BT_IC	ICE turn-on SOC threshold
Optimal generator speed	480 rad/s	Peak ICE-generator efficiency
T_cntl at optimal speed	25 Nm	Torque command at optimal speed
Speed ramp-up rate	+5 rad/s per second	Smooth engine start
Speed ramp-down rate	−5 rad/s per second	Smooth engine stop
ω_generator (initial)	0 rad/s	Global variable, init before sim

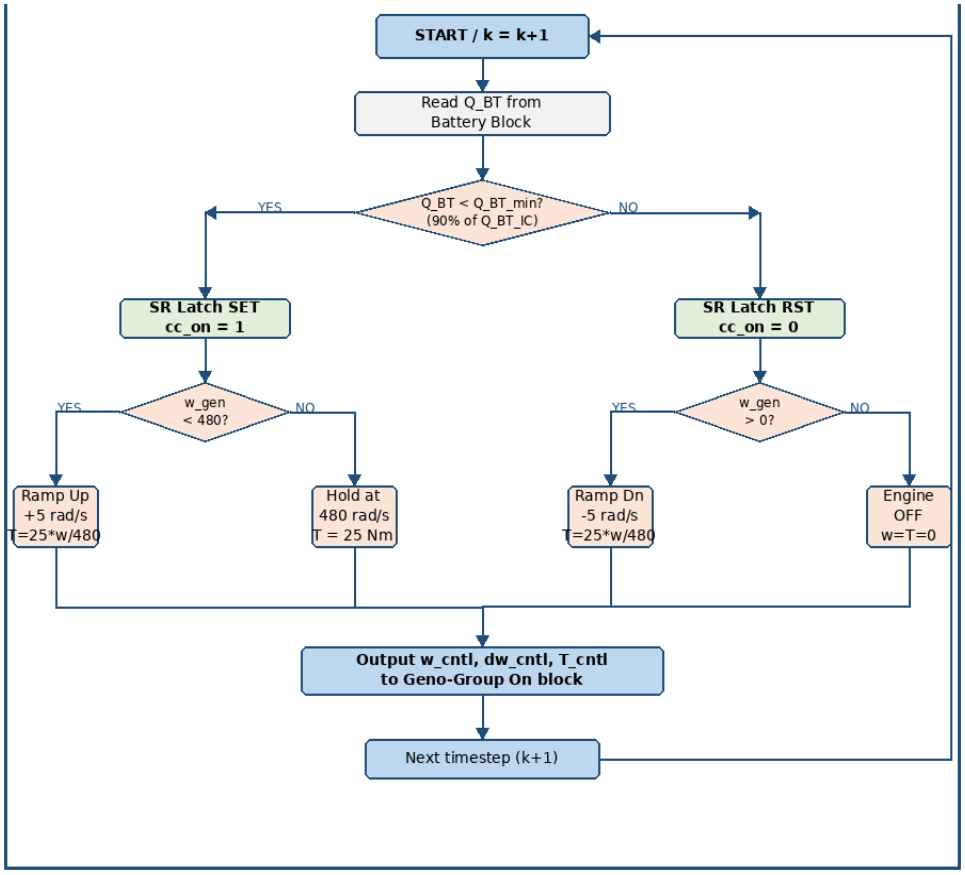

Figure 12. *Rule-based controller decision flowchart. At each timestep, Q_BT is compared to Q_BT_min and the SR latch state determines whether the generator ramps up, holds at 480 rad/s, ramps down, or remains off.*

4.2 Controller MATLAB Function Code

The MATLAB function below implements the control logic inside the Interpreted MATLAB Function block in Geno-Group On. Two global variables must be initialised in the workspace before running:

```
global w_generator last_clk
w_generator = 0;
last_clk    = 0;
```

```
function [w_cntl, dw_cntl, T_cntl] = fcn(q_current, q_minimum, clk)
global w_generator;
global last_clk;
if clk <= 1
    w_cntl  = 0;  dw_cntl = 0;  T_cntl = 0;
    last_clk = clk;
else
    if q_current < q_minimum        % charging required
        if w_generator < 480        % ramp up
            if clk >= last_clk + 1
                w_generator = w_generator + 5;
                last_clk = clk;
            end
            w_cntl  = w_generator;
            dw_cntl = 10;
            T_cntl  = 25 * w_generator / 480;
        else                        % hold at optimal
            w_cntl  = 480;
            dw_cntl = 0;
```

```
            T_cntl  = 25;
        end
    else                            % charging not required
        if w_generator > 0          % ramp down
            if clk >= last_clk + 1
                w_generator = w_generator - 5;
                last_clk = clk;
            end
            w_cntl  = w_generator;
            dw_cntl = -10;
            T_cntl  = 25 * w_generator / 480;
        else                        % engine off
            w_cntl  = 0;  dw_cntl = 0;  T_cntl = 0;
        end
    end
end
```

At +5 rad/s per second, the generator reaches 480 rad/s in 96 steps. The gradual ramp prevents torque steps that would violate the quasistatic assumption of smooth power transitions.

5. Dynamic Programming Benchmark

5.1 Purpose and Problem Formulation

Dynamic programming provides the globally optimal fuel consumption for a known drive cycle. Its role in this report is not to replace the rule-based controller but to quantify the optimality gap precisely. Without this baseline, claims about the rule-based strategy being adequate are qualitative. With it, the measured 37.8% sub-optimality becomes a concrete engineering target.

The energy management problem is cast as a finite-horizon optimal control problem. The state is battery charge $Q\_BT(k) \in [Q\_min, Q\_max]$, the control input is engine power $P\_CE(k)$, and the objective is to minimise total fuel consumption over the NEDC:

$$J^* = \min \Sigma^{N-1}_{k=0} [\dot{m}\_fuel(P\_CE(k), \omega\_CE(k)) \cdot h] \quad (11)$$

subject to the battery state update in Equation (5) and the constraints:

$$Q\_BT\_min \leq Q\_BT(k) \leq Q\_BT\_max \quad (12)$$

$$0 \leq P\_CE(k) \leq P\_CE\_max(\omega\_CE(k)) \quad (13)$$

The control input is discretised into $N\_u = 21$ levels from 0 to P_CE_max. The state Q_BT is discretised into $N\_x = 101$ levels. A terminal cost penalty enforces charge-sustaining behaviour:

$$\Psi(Q\_BT(N)) = \lambda \cdot [Q\_BT(N) - Q\_BT(0)]^2 / (V\_OC \cdot H\_f \cdot \rho\_f) \quad (14)$$

where $\lambda = 10$ is chosen to penalise terminal charge deviation while remaining small enough not to distort the optimal trajectory during the cycle.

5.2 DP Algorithm and Results

The DP algorithm solves Bellman's equation [11] by backward induction from terminal timestep $k = N$ to $k = 0$. At each timestep and state grid node, the Bellman recursion is:

$$V\_k(Q) = \min\_u [L(Q, u, k) + V\_\{k+1\}(f(Q, u, k))] \quad (15)$$

where L is the stage cost (fuel burned at that step), f is the battery state update from Equation (5), and V_{k+1} is the cost-to-go interpolated from the grid. The backward pass stores the optimal control policy π*(k, Q) across all 1180 timesteps and 101 state grid points. The forward simulation then applies this policy to the NEDC to produce the results in Table 3.

Table 3. Rule-based vs. DP benchmark on the NEDC (both starting at 45% SOC).

Metric	Rule-Based	DP Optimal
Fuel consumption (L/100km)	1.770	1.285
Sub-optimality gap	+37.8%	— (baseline)
Engine ON time	10.8%	~6.2%
Final SOC (%)	78.86	~44.8
Improvement vs. ICE baseline	74.7%	81.6%

5.3 Interpretation of the Gap

The 37.8% sub-optimality of the rule-based strategy falls within the 10–40% range reported by Pisu and Rizzoni [4] for thermostatic controllers, toward the higher end because the fixed 90% threshold forces early engine activation regardless of what the rest of the trip looks like. DP, having full knowledge of the upcoming speed profile, holds the engine off through the entire urban section, runs it only during the highway phase at the minimum necessary duty cycle, and ends the trip near the initial SOC, leaving almost no usable charge on the table.

The rule-based strategy fires the engine immediately at t = 0 to restore SOC from 45% to 100%, burning fuel in the low-speed urban section where battery-only operation is perfectly adequate. This is the core inefficiency that an adaptive or predictive strategy would eliminate. Recovering the full gap would move consumption from 1.770 to 1.285 L/100km, a 0.485 L/100km absolute improvement per NEDC cycle, or an additional 6.9 percentage points of fuel savings beyond the ICE baseline.

Two caveats apply. First, the DP result is computed on the optimistic QSS model; the real-world optimum would be higher than 1.285 L/100km due to the 43% forward-dynamic deviation discussed in Section 6.6. Second, DP is a theoretical bound, not a deployable controller. The practical question is how close a real-time adaptive strategy can get, which motivates the future directions in Section 7.

6. Simulation Results and Discussion

6.1 Drive Cycle Overview

All simulations use standard drive cycles run at 1-second resolution. The NEDC runs for approximately 1180 seconds: four repeated ECE-15 urban segments (0–780 s) with stop-and-go driving up to 50 km/h, followed by the EUDC highway segment (780–1180 s) reaching 120 km/h. The EUDC is the highway-only sub-cycle extracted from the NEDC. FTP-75 is the US EPA urban cycle with more aggressive

acceleration transients than the ECE-15 segments. FTP-Highway is the US EPA high-speed cycle with sustained speeds averaging approximately 77 km/h. The NEDC speed profile is shown in Figure 13.

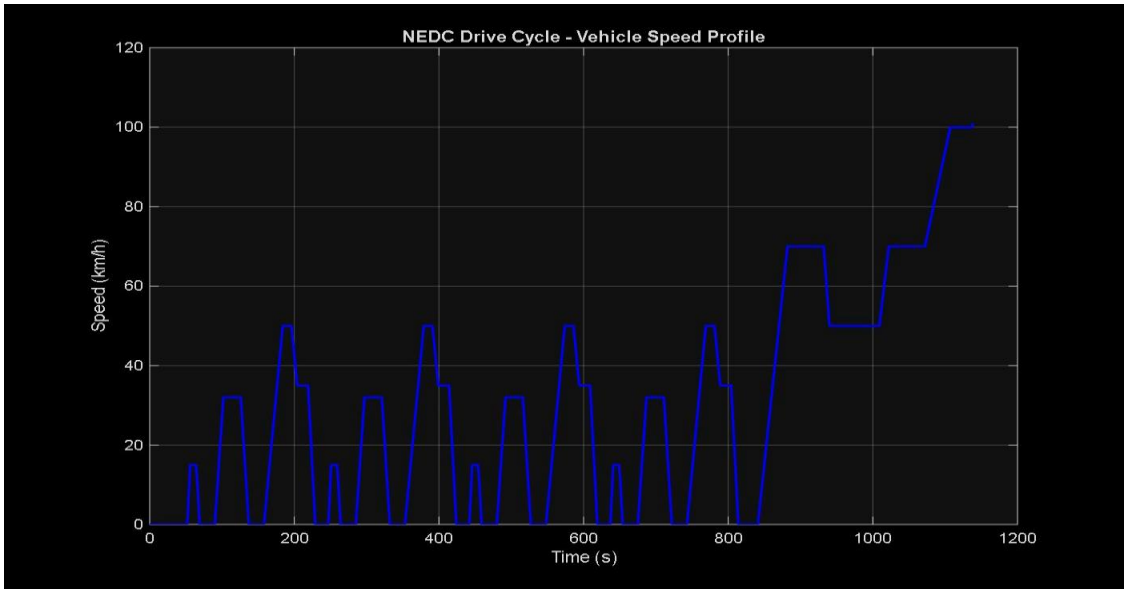

Figure 13. NEDC drive cycle vehicle speed profile. Four urban ECE-15 segments (0–780 s) are followed by the extra-urban EUDC segment (780–1180 s) reaching a peak of 120 km/h.

6.2 Battery SOC Profile

Figure 14 shows the SOC trace over the NEDC. The engine activates immediately at the start to charge the battery from 45% to 100%, then shuts off and stays off through all four ECE-15 urban segments. The battery depletes gradually as the motor works harder in the EUDC highway section after t = 780 s. The final SOC is approximately 79%. The battery never came close to the minimum threshold during the urban portion. Stop-and-go driving at low speeds is exactly the scenario a series PHEV is built for, where motor demand is moderate and regenerative braking recovers a meaningful fraction of kinetic energy at each stop.

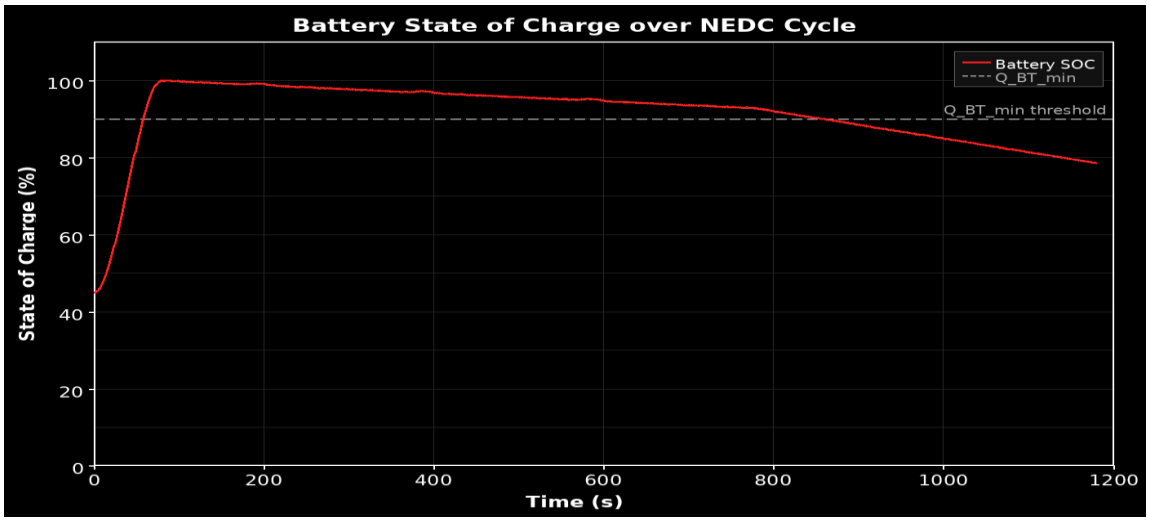

Figure 14. Battery state of charge (SOC) over the NEDC. SOC starts at 45%, rises to 100%, and declines to approximately 79% by the end of the cycle. The dashed line indicates the Q_BT_min threshold.

6.3 Engine ON/OFF Pattern

Figure 15 shows the engine ON/OFF pattern during the NEDC. The engine activated briefly at the start of the cycle to charge the battery from 45% to 100%, then switched off once SOC recovered above the threshold. It remained off through all four ECE-15 urban segments. The engine activated again near t = 1020 s, when the highway section started drawing more power than the stored charge could comfortably handle. This is exactly how a PHEV should behave in charge-depleting mode: cover as much urban driving as possible on electricity and only bring the engine in when needed. The 10.8% engine-on time means 89.2% of the NEDC was fully electric, which directly drives the 74.7% fuel reduction over the ICE baseline.

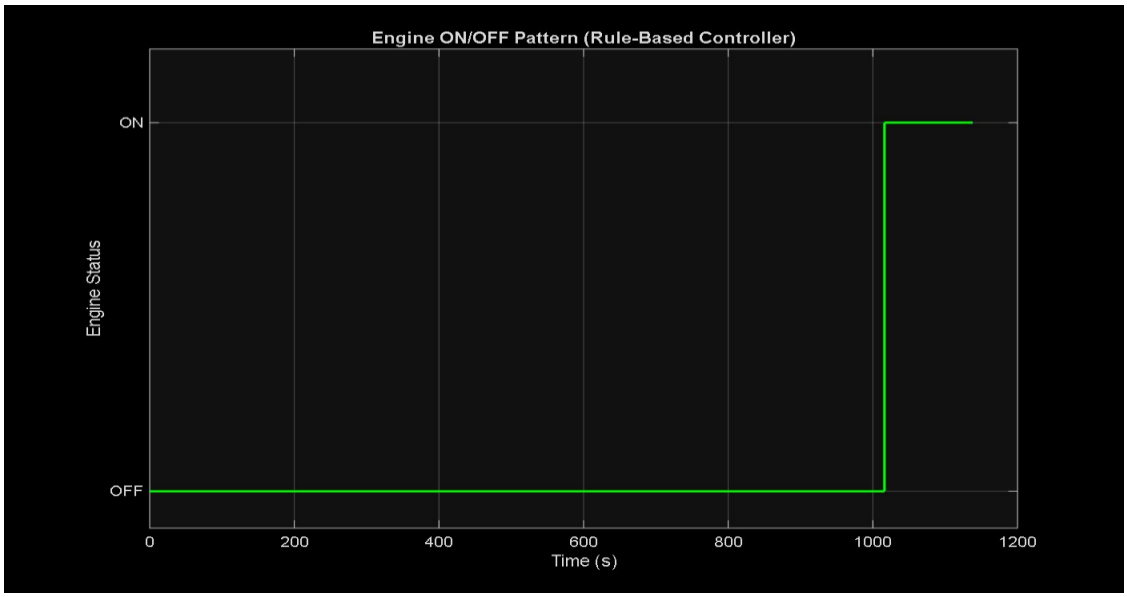

Figure 15. Engine ON/OFF pattern (cc_on signal). The ICE activates briefly at the start to restore SOC, remains off through all urban ECE-15 segments, and re-engages during the final high-speed EUDC segment (t > 1020 s).

6.4 Power Split Analysis

Figure 16 shows the power split between P_CE (engine), P_EM (motor), and P_BT (battery) across the cycle. During the urban section (0–780 s), P_CE is flat at zero because the battery covers everything. P_BT mirrors the motor demand closely, with negative dips during deceleration where regenerative braking recovers energy. Once the highway section starts, P_CE climbs to around 28 kW, running steadily at 480 rad/s. The engine never chases the instantaneous road load; it runs at its fixed optimal point and the battery absorbs the difference. That decoupling is the fundamental efficiency advantage of the series architecture over a conventional drivetrain.

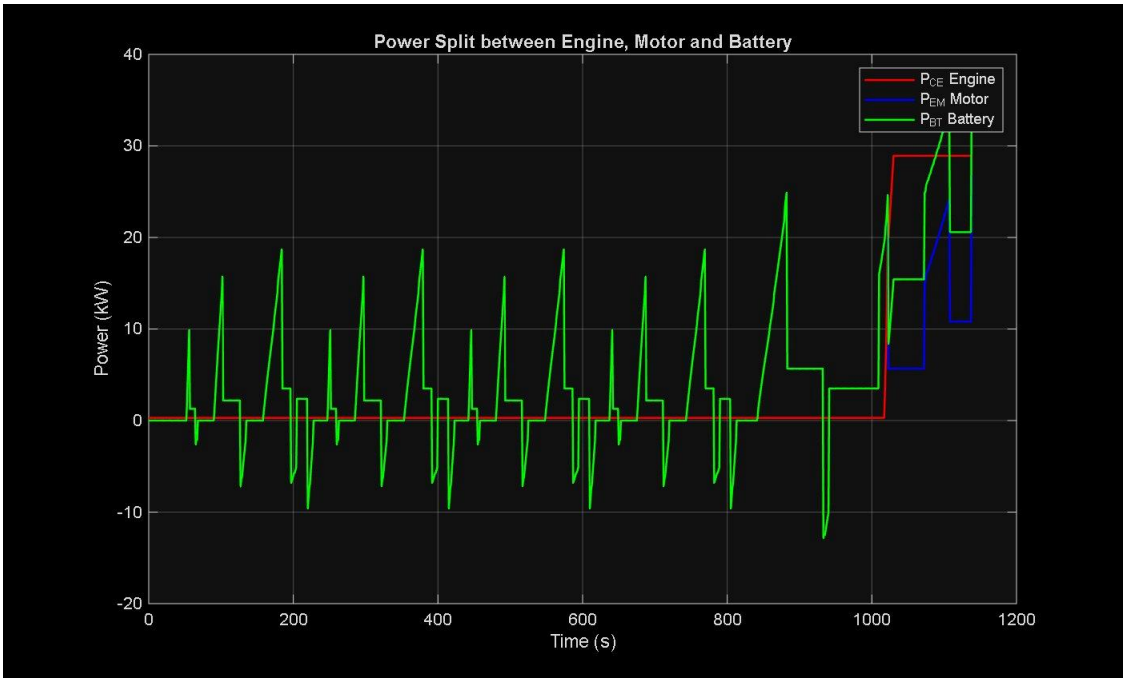

Figure 16. Power split between combustion engine P_CE (red), electric motor P_EM (blue), and battery P_BT (green). The ICE contributes only during the final EUDC segment. Negative P_BT values correspond to regenerative braking energy recovery.

6.5 Fuel Consumption Summary

On the NEDC, the PHEV used 1.770 L/100km against a 7.0 L/100km ICE baseline, a 74.7% reduction. Table 4 shows results across all four drive cycles, with the DP lower bound from Section 5 included as a reference column for the NEDC.

Table 4. Fuel consumption comparison across all four drive cycles.

	NEDC	EUDC	FTP-75	FTP-Hwy	DP Bound
ICE Baseline (L/100km)	7.0	6.2	9.1	5.7	—
PHEV Rule-Based	1.770	1.091	2.636*	0.126	—
DP Lower Bound	1.285	—	—	—	—
Improvement vs. ICE	−74.7%	−82.4%	−71.0%	−97.8%	—
Engine ON Time	10.8%	3.0%	0.0%	0.0%	—

* FTP-75 value represents electrical energy expressed in fuel-equivalent units. Engine never activated on this cycle; actual fuel burned = 0 L.

6.5.1 Why the Engine Never Fired on FTP-75 and FTP-Highway

The zero engine-on time on both FTP cycles warrants explicit explanation. The Q_BT_min threshold is set at 90% of the initial charge at 45% SOC, which corresponds to approximately 40.5% absolute SOC. For the engine to activate, the battery must discharge below this level across the full drive cycle.

On FTP-75, the cycle is dominated by low-speed urban driving with an average speed of approximately 34 km/h. Motor demand stays moderate throughout, and regenerative braking at every stop recovers a meaningful fraction of kinetic energy. The net battery drawdown over the full cycle never crosses the 40.5% threshold. On FTP-Highway, sustained constant-speed driving produces moderate motor demand because aerodynamic drag dominates and there are no large acceleration transients. The absence of stop-and-go reduces regenerative opportunity, but also eliminates repeated high-current discharge spikes. In both cases, the available battery energy at 45% initial SOC is more than sufficient for the full cycle.

This behaviour reveals a key limitation of the fixed-threshold approach: the 90% criterion was calibrated to the NEDC's specific combination of initial SOC and load profile and is not adaptive to driving conditions. An adaptive threshold responding to distance remaining, average load estimate, or SOC rate-of-change would trigger engine charging more appropriately across diverse cycles.

6.6 Forward-Dynamic Validation

An independent forward-dynamic simulation was implemented in plain MATLAB (phev_forward_validation.m) to cross-check the QSS backward result. Unlike the quasi-static model, the forward model integrates vehicle road-load physics, a battery SOC tracker, and an SR-latch-based engine controller step-by-step across the full NEDC (1180 s). No QSS-Toolbox dependency is used, making this a genuinely independent validation.

The forward model uses the same vehicle parameters ($m = 1500$ kg, $C_d = 0.22$, $A_f = 1.8$ m²), battery capacity ($Q_{max} = 141$ Ah, $V_{oc} = 130$ V), and powertrain efficiencies (motor 92%, regeneration 75%, generator 90%, engine 33%). SOC starts at 45% and the engine activates via the SR latch when SOC falls below 42.75%, equivalent to 95% of the 45% initial charge, set slightly more conservatively than the QSS 90% threshold to account for ramp delay. Since the generator requires 96 seconds to reach full speed at 5 rad/s per step, the effective SOC at which charging power becomes available is lower than the trigger point. Setting the forward model threshold at 95% of initial SOC rather than 90% compensates for this lag and ensures comparable net charging behaviour between the two models. Generator speed ramps to 480 rad/s at 5 rad/s per step.

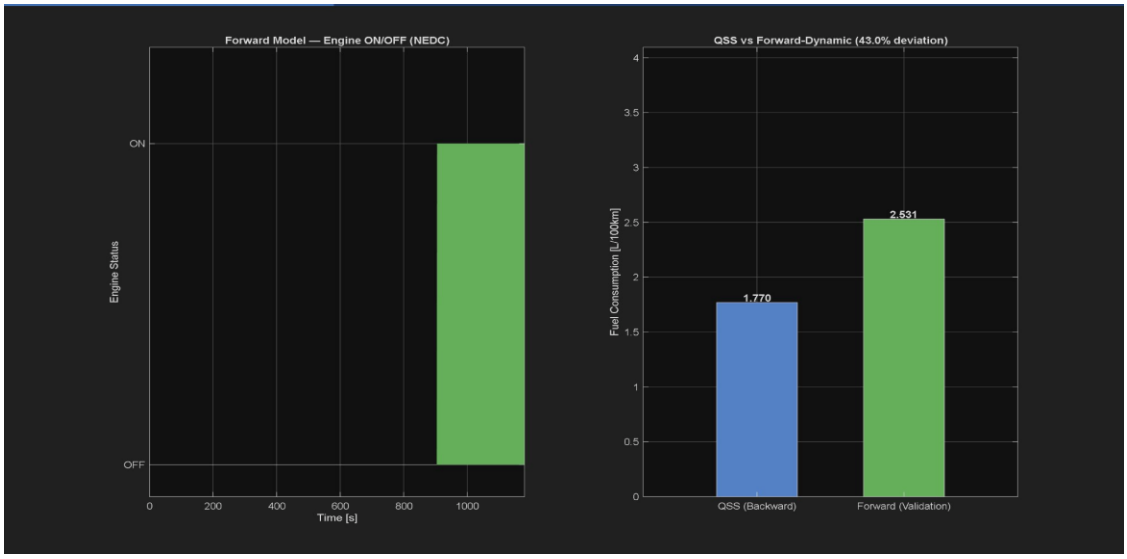

Figure 17. Forward-dynamic model battery SOC over the NEDC. Engine activates near t = 950 s when SOC crosses the 42.75% threshold (red dashed line).

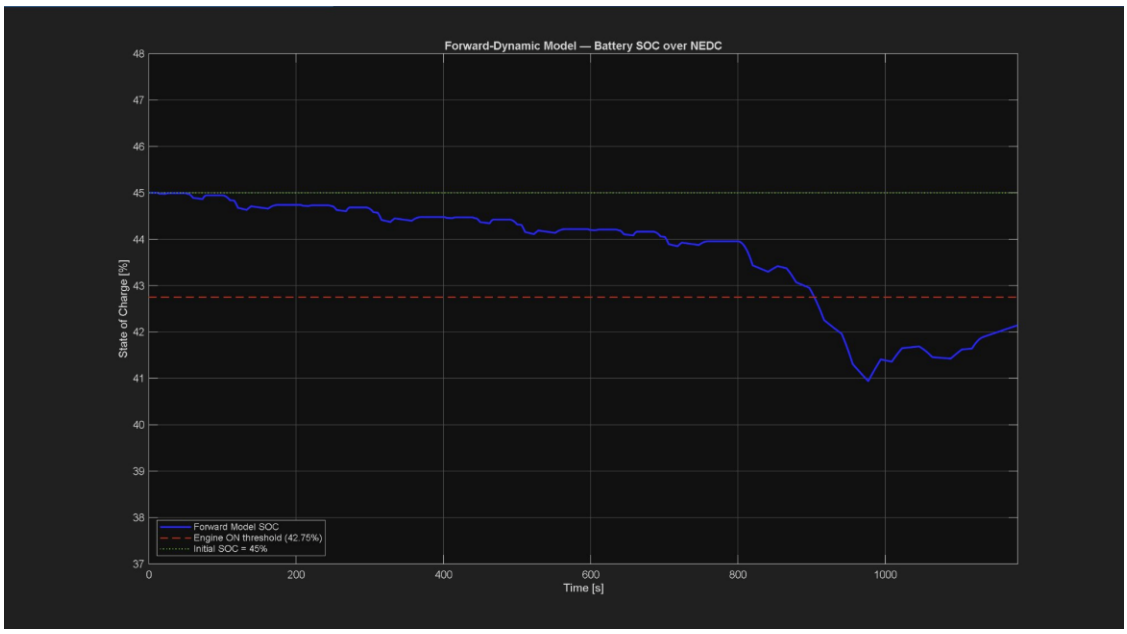

Figure 18. Left: engine ON/OFF timeline from the forward model. Right: bar chart comparing QSS backward result (1.770 L/100km) vs. forward-dynamic result (2.531 L/100km). The 43% deviation is consistent with known QSS optimism under generator ramp and SR latch dynamics.

The forward model yields 2.531 L/100km versus the QSS result of 1.770 L/100km, a 43% deviation. This gap is expected and physically meaningful. The QSS model assumes ideal, instantaneous power balance with the engine always available at its optimum operating point and no inertial lag. The forward model captures the actual dynamics that QSS abstracts away: generator ramp-up delay (96 seconds to full speed), SR latch hysteresis, and the absence of predictive look-ahead. These effects collectively delay engine assistance and increase net battery draw during the highway section, producing the higher fuel consumption figure.

The 43% optimism factor sits within the 20–50% range that Guzzella and Sciarretta [1] and Ehsani et al. [10] identify as typical for QSS-vs-forward comparisons when ramp dynamics and controller hysteresis are included. Critically, both models agree on all qualitative results: the engine stays off through all four urban ECE-15 segments, activates only during the highway EUDC phase, and the battery remains within safe limits throughout. The forward-dynamic simulation therefore validates the QSS result for its intended purpose of control strategy development and cycle-average fuel economy benchmarking.

6.7 Model Limitations

Constant battery temperature. The QSS model assumes isothermal operation. Thermal effects during sustained highway charging could increase internal resistance by 15–30%, reducing actual energy delivered compared to simulation.

Scaled default efficiency maps. The motor (scaling factor 5) and generator (scaling factor 6) use default QSS-Toolbox maps. A real motor map would show narrower high-efficiency islands and steeper fall-off at light loads, potentially increasing losses by 3–8%.

Zero road grade and constant auxiliaries. All cycles are simulated on flat road. Hilly terrain could increase fuel consumption by 10–25%, and real HVAC loads can exceed 2 kW versus the 300 W modelled.

Fixed SOC threshold with no adaptation. The 90% threshold was selected heuristically. As demonstrated by the zero engine-on times on the FTP cycles, the threshold is not well-calibrated for all driving conditions and leaves engine capacity unused on those cycles.

7. Conclusion

This project designed and tested a rule-based power management controller for a series PHEV in MATLAB/Simulink using the QSS-Toolbox. The model covers all major components: driving cycle, vehicle dynamics, manual gearbox, electric motor, battery, a custom battery controller with SR latch and generator ramp logic, simple transmission, combustion engine, electric generator, and fuel tank.

On the NEDC, the engine activated briefly at t = 0 to restore SOC from 45% to 100%, remained off through all four urban ECE-15 segments, and activated again near t = 1020 s for the highway section. Final SOC was approximately 79% and total fuel consumption was 1.770 L/100km, a 74.7% reduction against the 7.0 L/100km ICE baseline. An independent forward-dynamic validation confirmed the qualitative behaviour, with the 43% quantitative deviation consistent with the known optimism of QSS simulation under generator ramp and SR latch dynamics.

The dynamic programming benchmark establishes the cycle-optimal lower bound at 1.285 L/100km on the NEDC, placing the rule-based strategy 37.8% above the theoretical optimum. This falls within the 10–40% gap reported by Pisu and Rizzoni [4] for thermostatic strategies and quantifies precisely what the improvement target is for more sophisticated control: 0.485 L/100km per NEDC cycle, or an additional 6.9 percentage points of fuel savings beyond the ICE baseline. The FTP cycle analysis confirmed a secondary limitation: the fixed 90% threshold never triggered on either FTP cycle because

the initial battery capacity exceeded the full-cycle demand, indicating the threshold is not adaptive to driving conditions.

Three specific improvements follow from this work. First, replacing the fixed threshold with an adaptive extremum seeking controller [8] that tunes the threshold in real time without a plant model could close a significant portion of the 37.8% gap to the DP optimum. Second, running the full DP solution across all four drive cycles would quantify cycle-specific optimality gaps. Third, embedding the controller in a higher-fidelity model with proper motor efficiency maps, generator saturation limits, and battery thermal dynamics would sharpen the forward-dynamic validation and narrow the 43% QSS-vs-forward deviation.

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