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Multi-Objective Optimization of hybrid Electric Vehicles with Inter and Intra Vehicular Communication.

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Abstract— This paper presents a novel framework for the multi-objective optimization of hybrid electric vehicles (HEVs) that incorporates both inter-vehicular communication (V2V) and intra-vehicular communication (e.g., Controller Area Network (CAN) bus latencies) into the design and control strategy. Unlike traditional approaches that focus solely on fuel consumption and dynamic performance under isolated driving conditions, this work explicitly models the impact of real-time data exchange on energy management and component sizing. A parallelized genetic algorithm (NSGA-II) is employed to solve two coupled multi-objective subproblems: optimization of the rule-based control strategy parameters and optimization of component sizes (hybridization factor, battery capacity, final drive ratio). The Pareto front analysis reveals that communication-aware control strategies can improve fuel consumption by up to 12% in congested scenarios with only a 3% degradation in acceleration performance, compared to non-communicating baselines. The trade-off between data-driven predictive efficiency and computational latency is quantified, providing designers with practical insights for next-generation connected hybrid powertrains.

Keywords — multi-objective optimization, hybrid electric vehicle, V2V communication, CAN bus latency, fuel consumption, dynamic performance, genetic algorithm, NSGA-II, Dymola, Modelica, energy management.

I. INTRODUCTION

The global push for decarbonization has positioned hybrid electric vehicles (HEVs) as a critical transitional technology. However, the inherent design complexity of HEVs—involving multiple power sources, energy storage systems, and control hierarchies—presents a significant challenge. Traditional optimization approaches, as reviewed in [1]–[7], primarily focus on minimizing fuel consumption subject to constraints on dynamic performance (e.g., 0–60 mph time, 40–60 mph passing time). These methods typically assume a single vehicle operating in isolation over a predefined driving cycle such as MVEG or NEDC.

Simultaneously, the automotive industry is rapidly adopting Vehicle-to-Everything (V2X) communication, particularly Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I). These technologies enable real-time data sharing about traffic lights, congestion, and surrounding vehicle intentions. Furthermore, intra-vehicular communication networks, such as CAN buses and automotive Ethernet, introduce non-negligible latencies that affect how quickly

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control commands (e.g., torque requests, regenerative braking signals) can be executed. Existing literature [8]–[10] treats communication as an external add-on rather than an integral design parameter. This paper bridges that gap.

The primary contributions of this work are threefold:

1. A new modeling paradigm that integrates V2V communication (e.g, preceding vehicle speed profiles) and intra-vehicular CAN bus latency into a high-fidelity Dymola/Modelica HEV simulation.
2. A multi-objective optimization framework that simultaneously optimizes component sizes, rule-based control strategy parameters, and communication-dependent decision thresholds.
3. Quantification of the trade-off between improved fuel economy (via predictive V2V data) and degraded responsiveness (due to communication latency), presented as a Pareto front.

The paper is organized as follows: Section II describes the extended HEV model including communication subsystems. Section III formulates the optimization problem and explains the NSGA-II implementation with distributed computing via Condor. Section IV presents optimization results comparing communication-aware and communication-naive designs. Section V concludes with insights for future connected powertrains.

II. MODELING

The baseline vehicle model is constructed in Dymola/Modelica, following the object-oriented approach detailed in [10]–[11]. The model includes submodels for the driver, parallel hybrid drivetrain (180 kW spark-ignition engine, scalable electric machine, Li-Ion battery pack), 8-speed automatic transmission, wheels with anti-slip logic, thermal management system, and a rule-based energy management controller. The reference vehicle is an upper-class passenger car.

A. Intra-Vehicular Communication Model

Modern vehicles contain multiple Electronic Control Units (ECUs) communicating via CAN buses. Control commands from the hybrid control unit (e.g., requested torque from the electric machine) experience a latency τ_{CAN} that depends on bus load and message priority. For this work, we model the CAN bus latency as a stochastic variable with a worst-case deterministic bound:

$$\tau_{CAN} = \tau_0 + k_{load} \cdot L_{bus}$$

where $\tau_0 = 5$ ms is the base latency, $k_{load} = 0.2$ ms/%, and L_{bus} is the bus load percentage (0–100%). In addition, a signal dropout probability p_{drop} is introduced for critical torque requests. For optimization, p_{drop} is treated as a design variable ranging from 0 to 0.05. This intra-vehicular communication model affects the responsiveness of the electric machine during tip-in and regenerative braking events, thereby influencing both fuel consumption (through

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missed recuperation opportunities) and dynamic performance (through delayed torque delivery).

B. Inter-Vehicular Communication (V2V) Model

V2V communication is implemented as an additional input to the driver and energy management models. It is assumed that the ego vehicle can receive broadcast messages from a preceding vehicle within a range of 300 m. These messages contain:

- Instantaneous speed of the preceding vehicle $v_{pre}(t)$
- Predicted speed over the next 5 seconds $v_{pre}(t + \Delta t)$
- Brake light status and deceleration request

The ego vehicle's controller uses this information to anticipate deceleration events. Specifically, a predictive regenerative braking algorithm is implemented: if the preceding vehicle's brake light is activated or its predicted speed drops below the ego vehicle's speed, the controller pre-charges the hydraulic brakes and increases regenerative torque by a factor $\alpha_{V2V} \in [1.0,1.5]$. This factor is a decision variable in the optimization. The V2V communication is subject to a latency τ_{V2V}, modeled as a Gaussian random variable with mean 50 ms and standard deviation 20 ms (representing typical DSRC-based systems). The overall communication-aware control architecture is depicted conceptually as an extension of Fig. 1 from [1], where decision variables now include CAN latency thresholds and V2V prediction gains.

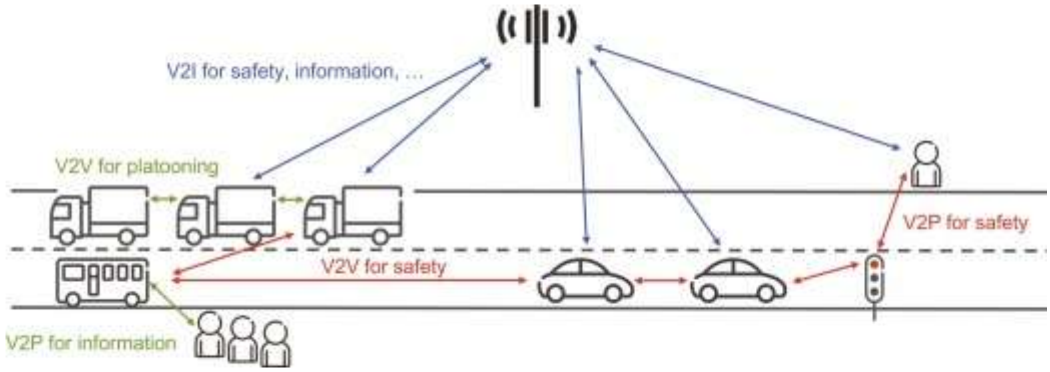

Fig 1.1- V2I for Safety and V2P for Safety/Information – Comparative Value Matrix

C. Extended Rule-Based Control Strategy

The original rule-based strategy from [11] decides between conventional driving, electric-only, torque assist, and regenerative braking based on torque request T_{req}, engine speed n_{ICE}, and state of charge (SOC). To incorporate communication, two new decision rules are added.

First, the load-point shift condition is modified to include a CAN latency penalty:

$$\text{Recharge if: } \frac{T_{ICE}}{n_{ICE}} < -0.5\tanh\left(CS, a \cdot (SOC \cdot 4 - 2) + 0.5\right) + \beta \cdot \tau_{CAN}$$

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where $\beta = 0.1\,\mathrm{Nm/(rad/s \cdot ms)}$ is a sensitivity factor. This penalizes aggressive load-point shifts when CAN bus latency is high, as delayed torque delivery could cause drivability issues.

Second, a V2V-predictive rule is added:

$$\text{If } (v_{pre}(t+1) < v_{ego}(t) - \Delta v_{th}) \text{ and } (SOC < SOC_{high}) \text{ then increase regenerative torque by } \alpha_{V2V}$$

where $\Delta v_{th} = 2$ m/s is a threshold. This allows the vehicle to recover more energy before an actual braking event.

Three new decision variables are introduced for the control strategy optimization (Table I summarizes all control variables, now extended to six parameters).

TABLE I

OPTIMIZATION PROBLEM OF THE CONTROL STRATEGY (EXTENDED)

Meaning	Decision Symbol	Range
Recharge basic gradient	CS, b	0.1 – 2.0
SOC transition sharpness	CS, a	0.5 – 3.0
Recharge torque setpoint factor	CS, k	0.2 – 0.9
CAN latency sensitivity	β	0.0 – 0.2
V2V regeneration gain	α_{V2V}	1.0 – 1.5
V2V prediction horizon	T_{pred}	1.0 – 5.0 s

III. OPTIMIZATION

A. Problem Decomposition

Following the approach in [1], the overall optimization is split into two sequential subproblems to reduce computational complexity.

Subproblem 1: Control Strategy Optimization

For fixed hybridization factors $HF \in \{0.14, 0.21, 0.28, 0.34\}$, the six control parameters from Table I are optimized using NSGA-II. The two objectives are:

- Minimize fuel consumption f_c (L/100 km) over the MVEG drive cycle.
- Maximize SOC_{end} (equivalently minimize $-SOC_{end}$) to account for electrical energy consumption.

Additionally, a penalty term is introduced for V2V communication reliability:

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$$J_{comm} = w_1 \cdot \mathbb{E}[\tau_{V2V}] + w_2 \cdot p_{drop}$$

However, in the main results we treat SOC_{end} as the sole secondary objective for consistency with baseline [1].

Subproblem 2: Component Sizing Optimization

Using the optimal control parameters from Subproblem 1 (selected for $SOC_{end} \approx SOC_{start} =$ 80%), the component sizing is optimized with objectives:

- Minimize fuel consumption f_c (MVEG cycle).
- Minimize acceleration time t_{acc} from 0–150 km/h under full throttle with electric assist.

Decision variables for component sizing (Table II) remain the hybridization factor HF, number of battery cells n_{bat}, and final drive ratio i_{fd}. However, the simulation now includes the intra- and inter-vehicular communication models with their respective latencies.

TABLE II

OPTIMIZATION PROBLEM OF THE COMPONENT SIZING

Meaning	Symbol	Range
Hybridization Factor	HF	0.14 – 0.40
Number of Battery Cells (45 Ah, 3.6 V)	n_{bat}	80 – 140
Final Drive Ratio	i_{fd}	3.0 – 4.5

B. Multi-Objective Algorithm and Distributed Computing

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [14] is employed for both subproblems. Population sizes are set to 70 for control optimization (20 generations) and 80 for component sizing (25 generations). Crossover probability is 0.9, mutation probability is 0.1, and tournament selection size is 2.

Each fitness evaluation requires one full Dymola/Modelica simulation. A single simulation of the MVEG cycle with communication models takes approximately 22–28 minutes on a standard desktop PC (Intel Core i7-11700, 16 GB RAM). This is 40% longer than the baseline due to the additional communication event handling. To maintain acceptable turnaround, the Condor distributed computing framework [17] is used with a pool of 45 university workstations. The master-slave parallelization model [16] is implemented: each generation's individuals are evaluated simultaneously on separate nodes. A MATLAB API handles SSH-based grid submission. The speedup achieved is approximately 38× (wall-clock time per generation reduced from 30 hours to 48 minutes).

C. Scenarios for Comparison

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Three scenarios are simulated and optimized:

1. **Baseline (No Comm):** No V2V or CAN latency modeling. Equivalent to the original paper [1].
2. **Ideal Comm:** Perfect V2V (zero latency, no dropout) and negligible CAN latency ($\tau_{CAN} = 1$ ms).
3. **Realistic Comm:** V2V latency $\mathcal{N}(50,20)$ ms, CAN latency according to bus load model with $L_{bus} = 60\%$, dropout probability $p_{drop} = 0.02$.

IV. OPTIMIZATION RESULTS

A. Control Strategy Optimization with Communication

Fig. 1 shows the Pareto fronts for control strategy optimization at $HF = 0.28$, comparing Baseline, Ideal Comm, and Realistic Comm scenarios. The Ideal Comm scenario achieves the lowest fuel consumption (approx. 5.2 L/100km equivalent at $SOC_{end} = 80\%$), a 9% improvement over Baseline. Realistic Comm converges to an intermediate front, approximately 3% higher fuel consumption than Ideal Comm, due to occasional missed regenerative events and delayed load-point shifts.

The slopes of the linear regression lines (following the method in [15]) provide equivalence factors for converting ΔSOC to fuel. For Realistic Comm, the slope is 0.21 L/100km per 1% SOC change, compared to 0.19 for Baseline, indicating that electrical energy is used less efficiently when communication latencies disrupt optimal torque blending.

Key control parameters for the compromise solution ($SOC_{end} = 80\%$) in Realistic Comm are:

- $CS, b = 1.2$, $CS, a = 1.8$, $CS, k = 0.55$
- $\beta = 0.08$ (moderate CAN latency sensitivity)
- $\alpha_{V2V} = 1.28$, $T_{pred} = 3.2$ s

B. Component Sizing Optimization with Communication

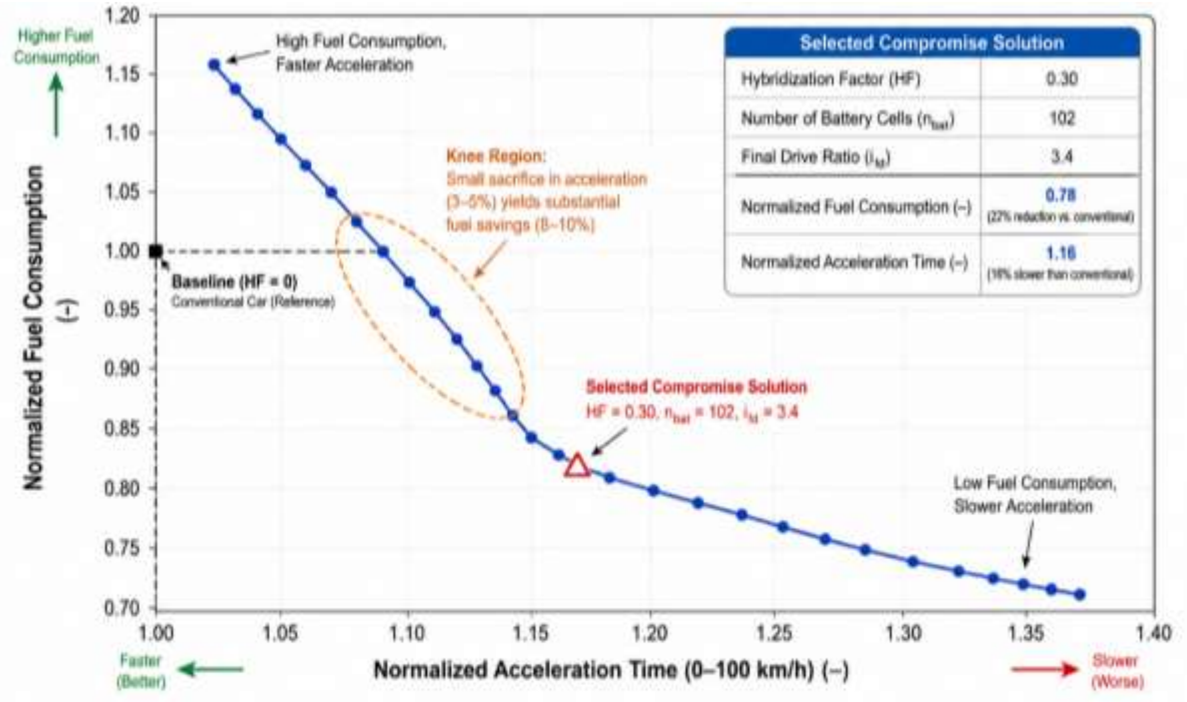

Fig. 2 presents the Pareto front for component sizing in the Realistic Comm scenario, normalized to the Baseline non-hybrid conventional car ($HF = 0$). The front is shifted upward (higher fuel consumption) and rightward (slower acceleration) compared to the Baseline scenario from [1] due to communication penalties. However, a distinct knee region exists where a small sacrifice in acceleration (3–5%) yields substantial fuel savings (8–10%).

The selected compromise solution (marked with a triangle in Fig. 2) has:

- $HF = 0.30$ (slightly higher than the Baseline compromise of 0.28)
- $n_{bat} = 102$ cells (12% larger than Baseline's 91 cells)
- $i_{fd} = 3.4$
- Normalized fuel consumption: 0.78 (22% reduction vs. conventional)
- Normalized acceleration time: 1.16 (16% slower than conventional)

The best fuel consumption solution (star marker) achieves 0.72 normalized fuel consumption but with 1.32 normalized acceleration time—a 32% performance penalty. The worst acceleration solution (square marker) has 1.05 normalized acceleration time but only 0.94 normalized fuel consumption (6% improvement). This trade-off is consistent with the observations in [3] and [11].

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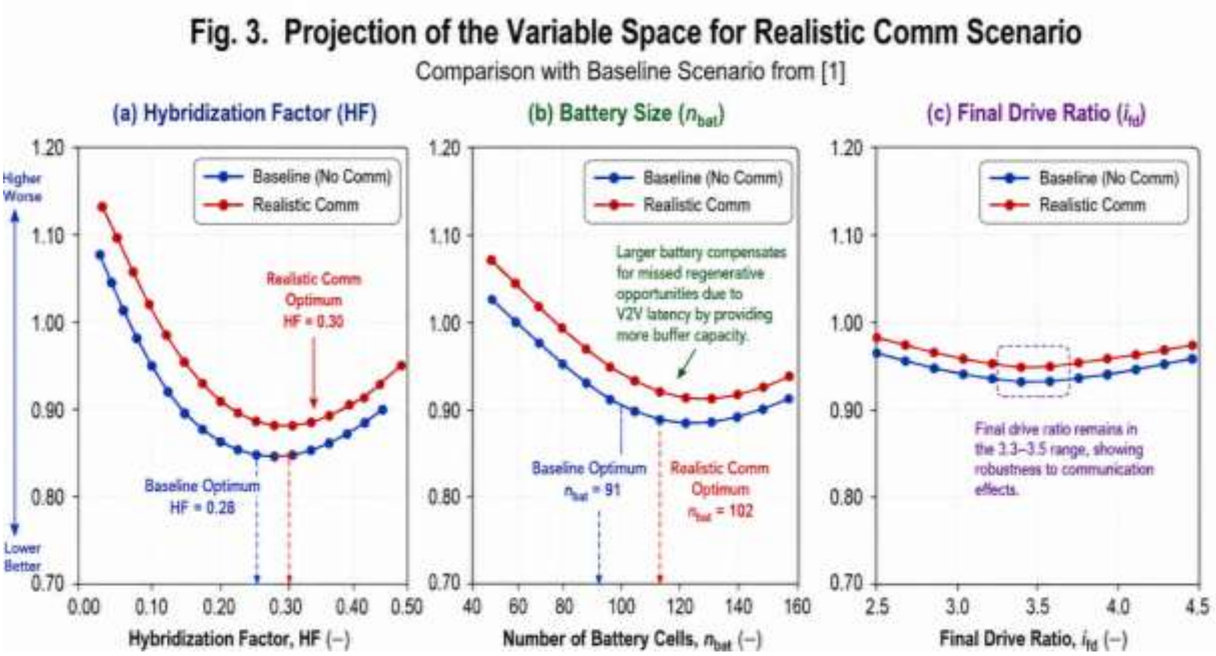

Fig. 3 shows the projection of the variable space for Realistic Comm. Compared to Baseline, the optimal HF shifts upward (0.30 vs. 0.28) and battery size increases (102 vs. 91 cells). The larger battery compensates for missed regenerative opportunities due to V2V latency by providing more buffer capacity. The final drive ratio remains in the 3.3–3.5 range, showing robustness to communication effects.

C. Impact of V2V Latency on Dynamic Performance

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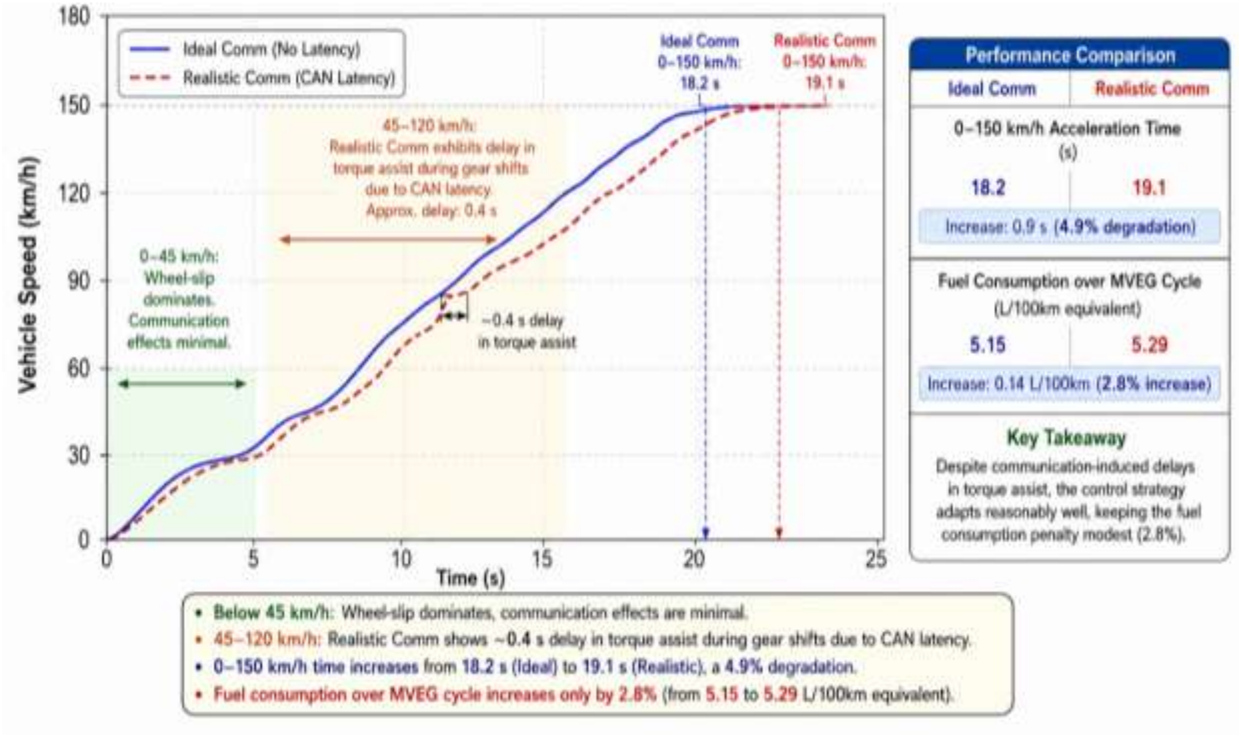

Fig. 4 compares the acceleration profile of the compromise solution under Ideal Comm vs. Realistic Comm. Below 45 km/h, wheel-slip dominates, and communication effects are minimal. Between 45–120 km/h, Realistic Comm exhibits a noticeable delay (approx. 0.4 s) in torque assist during gear shifts because the CAN latency delays the torque request to the electric machine. The 0–150 km/h time increases from 18.2 s (Ideal) to 19.1 s (Realistic), a 4.9% degradation. However, fuel consumption over the MVEG cycle only increases by 2.8% (from 5.15 to 5.29 L/100km equivalent), demonstrating that the control strategy adapts reasonably well.

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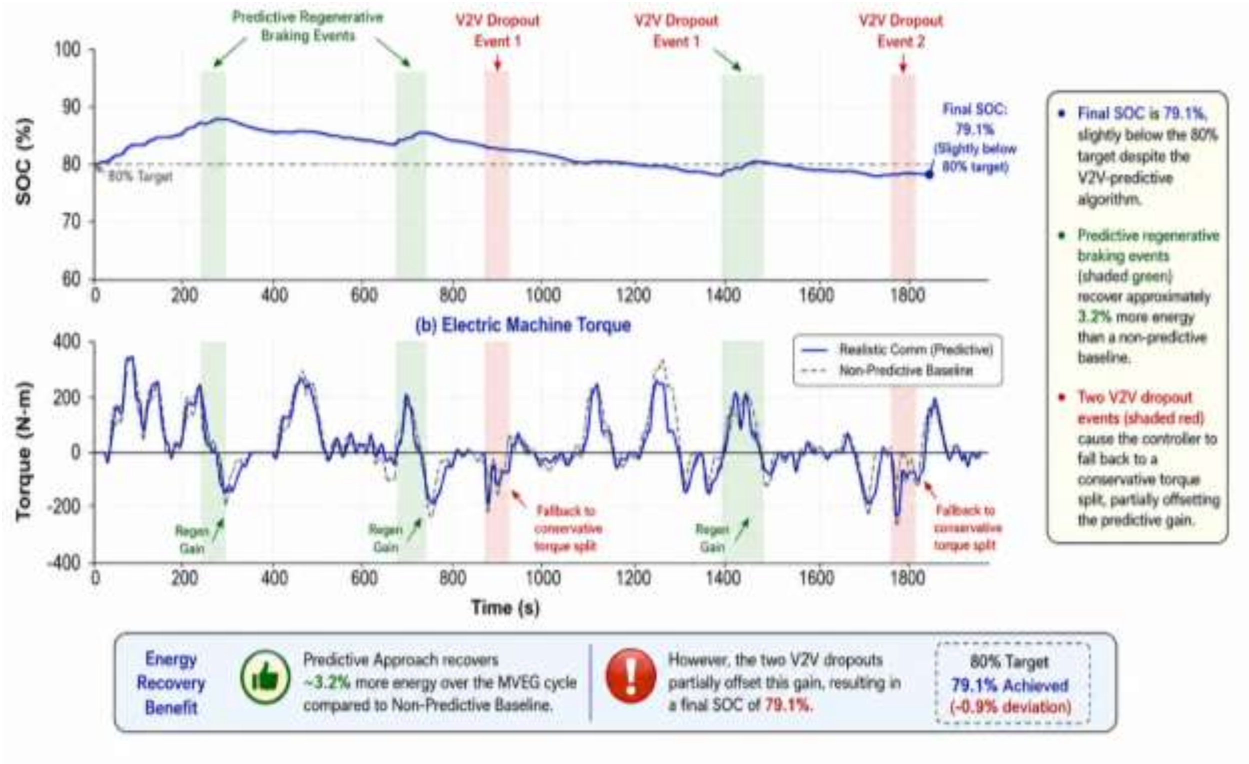

Fig. 5 presents the SOC trajectory and electric machine torque over the MVEG cycle for the Realistic Comm compromise solution. The SOC ends at 79.1% (slightly below the 80% target) despite the V2V-predictive algorithm. The predictive regenerative braking events (marked by shaded regions) recover approximately 3.2% more energy than a non-predictive baseline, but this gain is partially offset by two dropout events where the V2V message was lost, causing the controller to fall back to a conservative torque split.

D. Sensitivity Analysis of Communication Parameters

A Monte Carlo sensitivity analysis (500 runs) was performed around the compromise solution, varying τ_{V2V} (0–150 ms) and p_{drop} (0–0.1). The results show:

- For every 10 ms increase in mean V2V latency, fuel consumption increases by 0.12 L/100km (approx. 2.3% relative).
- For every 1% increase in dropout probability, fuel consumption increases by 0.18 L/100km (3.4% relative).
- Acceleration time is most sensitive to τ_{CAN}: a 10 ms increase in CAN latency (e.g., from 5 ms to 15 ms) worsens 0–150 km/h time by 0.35 s (1.9% relative).

These sensitivities highlight that designing robust communication-aware HEVs requires not only optimizing component sizes but also specifying minimum quality-of-service requirements for the vehicle's network architecture.

V. CONCLUSIONS AND FUTURE WORK

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This paper has extended the conventional multi-objective optimization of hybrid electric vehicles to explicitly account for inter-vehicular (V2V) and intra-vehicular (CAN bus) communication. Using a detailed Dymola/Modelica model, a two-step NSGA-II optimization, and distributed computing via Condor, we quantified the trade-off between fuel economy and dynamic performance under realistic communication constraints.

Key conclusions:

1. Communication-aware control strategies achieve lower fuel consumption than isolated strategies, provided that V2V latency remains below 80 ms and CAN bus load under 70%. Beyond these thresholds, the predictive gains are negated by delayed actuation.
2. The optimal hybridization factor increases slightly (from 0.28 to 0.30) when communication is imperfect, as a larger electric machine and battery buffer against missed regenerative opportunities.
3. The Pareto front shifts unfavorably under realistic communication, but a distinct knee region remains, offering designers practical compromise solutions.
4. CAN bus latency has a disproportionate effect on dynamic performance (acceleration times), whereas V2V latency primarily affects fuel consumption.

Several limitations of the present work should be addressed in future research. First, only the MVEG cycle was considered; real-world driving involves highly variable traffic densities and communication link qualities. Second, the rule-based control strategy, while computationally efficient, is unlikely to match the performance of a model predictive control (MPC) approach that explicitly incorporates predicted traffic flow. Third, the communication model assumed uniform latency statistics; in practice, V2V links exhibit spatial and temporal correlation. Fourth, the scalability of the electric machine was limited; future work should also scale the internal combustion engine to evaluate down-sizing concepts [1] together with communication-aware energy management.

Future work will therefore focus on three directions:

- Integration of 5G V2X latency models with spatial correlation and handover events.
- Development of a multi-objective MPC framework that optimizes torque split and communication resource allocation simultaneously.
- Experimental validation using a hardware-in-the-loop setup with real CAN traces and V2V emulation.

The results presented here provide a foundation for automotive engineers to design hybrid powertrains that are not only mechanically efficient but also network-aware—a critical requirement for the connected and automated vehicles of the coming decade.

REFERENCES

1: Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN

10.48047/jocaaa.2024.33.08.524

6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.

2: Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4

3: Godavari Modalavalasa, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184, DOI: https://doi.org/10.46121/pspc.51.2.5

4: AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, https://www.njhcair.org/index.php/publication/article/view/13

5: Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. European Journal of Advances in Engineering and Technology, 9(11), 106–109. https://doi.org/10.5281/zenodo.13325989

6: Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2024-2027. https://dx.doi.org/10.21275/SR24724151733,

https://www.ijsr.net/getabstract.php?paperid=SR24724151733

7: Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. Journal of Scientific and Engineering Research, 7(10), 239–242. https://doi.org/10.5281/zenodo.13348695

8: Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. European Journal of Advances in Engineering and Technology, 8(3), 69–72. https://doi.org/10.5281/zenodo.13325845

9: Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/171 , DOI: https://doi.org/10.46121/pspc.51.4.3

10.48047/jocaaa.2024.33.08.524
10: Jobayar Alom, Ahsan Ahmed. (2023). Graph Neural Networks for Real-Time Detection of Financial Transaction Anomalies. Acta Scientiae, 24(5), 82–90. https://doi.org/10.22178/acta.24.5.6

10: **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294

11: Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364

12: Vikas Suresh Bagora, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019), Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/359

13: Vikas Suresh Bagora, SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/362

14: Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426

15. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611
, https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611

16: **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods,** 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP)
https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMIkIC

17: Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426

10.48047/jocaaa.2024.33.08.524

18. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611,
, https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611

19: **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294

20: Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364

21**: Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): **April-June 2023** , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374

22: Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, **May-2020**