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RESEARCH ARTICLE

Connected and Autonomous Vehicle Cohort Speed Control Optimization via Neuroevolution

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ABSTRACT Predictive Energy Management (PrEM) research is at the forefront of modern transportation's energy consumption reduction efforts. The development of PrEM optimization algorithms has been tailored to selfish vehicle operation and implemented in the form of vehicle dynamics and/or adaptive powertrain control functions. With the progress in vehicle automation, this paper focuses on extending PrEM into the realm of a System of Systems (SoS). The proposed approach uses the shared information among Connected and Automated Vehicles (CAV) and the infrastructure to synthesize a reduced energy speed trajectory at the cohort level within urban environments. Neuroevolution is employed to incorporate a generalized optimum controller, robust to the emergent behaviors typical of multi-agents SoS. The authors demonstrated the use of heuristics and systems engineering processes in abstracting and integrating the resulting neural network within the control architecture, which enables novel added-value features such as green wave pass/fail classification and e-Horizon velocity prediction. The resulting controller is faster than real-time and was validated with a multi-agent simulation environment and on a real-world closed-loop track at the American Center for Mobility (ACM). The GM Bolt and Volt CAV mixed cohort testing at ACM demonstrated energy reductions from 7% to 22% depending on scenarios.

INDEX TERMS Minimum energy control, optimal control, intelligent systems, artificial intelligence, mobile robots, systems engineering

I. INTRODUCTION

Advances in vehicle and powertrain control systems and autonomous vehicles pave the way for cleaner and more sustainable transportation solutions. Predictive Energy Management (PrEM) enables conventional and electrified vehicles to maintain close to optimal efficiency across a broader range of operating conditions. Complex powertrains, such as hybrids, are optimized and calibrated around a set of known drive cycles (e.g., Federal Test Procedures). Due to the stochastic nature of real-world driving conditions, adaptively changing torque split calibration on the fly has yielded more consistent efficiency improvement, achieving up to 4% additional energy reduction [1].

On the vehicle dynamic PrEM side, the automation of vehicles provides the opportunity to achieve vehicles' dynamic behaviors that mitigate the strong impact of human driving style and aggressiveness on energy consumption [2], [3]. Vehicle dynamics-based approaches have been developed for selfish vehicle operation where a vehicle attempts to achieve its ''own selfish'' optimal velocity profile [4], [5]. Due to the wide range of vehicle classes and powertrain types on the road, heterogeneous selfish behavior does not necessarily translate to an optimal solution globally. It can result

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in increased energy consumption as high as 10% [6]. The authors stipulate that a solution considering traffic emergent behavior can viably provide both sustained and higher global energy reduction performance across heterogeneous vehicle types while still enabling local adaptive powertrain optimization. Vehicle automation and connectivity provide the necessary building blocks to enable the proposed SoS operation, where a group of Connected Automated Vehicles (CAV, here referred to as the ''cohort'') collaborates around their perception of the world to find a common optimal energy footprint. In doing so, this research focuses on optimizing traffic light eco-approach, which is critical to avoid congestion, long idling time, and inefficient stop and go behaviors in the cities [4], [5], [7]. Prior work such as the Green Wave method relies on a fix and rigid synchronization to minimally disrupt traffic flow [5]. Self-organizing and Deep Learning with Dynamic Programming (DP) methods have been shown to scale these benefits using connectivity, where a sensors network is used to characterize the traffic flow incoming to the intersections [4], [7]. In this paper, the authors demonstrate that Neural Networks can directly learn to infer optimal strategies without any external optimization results such as that provided by conventional optimal control algorithms. We claim that cellular network-based information sharing between the cohort lead vehicle and the infrastructure and vehicle-to-vehicle communication enables real-time speed optimization across any traffic light network. We assume that the cohort is already formed, referring the reader to the following [8], [9] for formation strategies.

The authors demonstrate that Neuroevolution can directly learn from the interaction between complex systems and their stochastic environments and that it does not require any plant model simplification or translation into an optimization program. This work provides a novel approach to developing faster than real-time vehicle level control functions, enabling new and unique added value features supporting local adaptive powertrain functions. Simulation is here used to train and develop the speed controller via neuroevolution. The embedded controller is also validated on test vehicles around a closed-loop track. The rest of the paper consists of the problem description and synthesis in the following section II, followed by the application of Neuroevolution in section III. The simulation and road test results are presented in section IV. Finally, we conclude in section V.

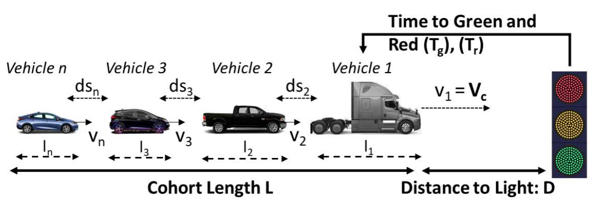

FIGURE 1. Light and heavy-duty vehicle cohort characteristics.

II. PROBLEM DEFINITION AND SYNTHESIS

The proposed CAV SoS combines SAE Level 3 vehicles operation with infrastructure connectivity. Safe vehicle-to-vehicle distance is maintained via Adaptive Cruise Control (ACC). In doing so, the AV stack enables safe autonomy at the vehicle level. The CAVs' lead vehicle receives information from the connected traffic lights along the route via a cellular network (Fig. 1). The goal is to control the cohort speed as a single entity and reduce its global energy consumption while enabling any local PrEM powertrain function to adapt its energy management strategy locally by receiving a predicted speed e-Horizon. At the cohort level, speed optimization aims to reduce the number of acceleration and deceleration events as the predominant road load term for city driving. These events can be minimized by achieving a ''green wave'' through the traffic light network. The AI learning objective function (LOF) is built on the ability of the entire cohort to pass within the green light window (the reward) while minimizing its dynamic energy demand as follows:

$$LOF = Reward - \int_{t=0}^{T} V_c \times |A_c| \, dt \tag{1}$$

when V_c and A_c are the cohort speed and acceleration, respectively. The reward is a fixed value if successful or zero otherwise. It forces the controller to pass the green light and built up speed while the energy term forces the system to minimize inefficient speed fluctuations. Note that the authors prove that this equation directly correlates to fuel efficiency improvement in the validation section (see Fig. 7).

The SoS architecture is designed around each autonomous agent's ability to safely follow each other, which consequently enables the problem to be abstracted around a simpler set of learning parameters, shown in Table 1. The number of vehicles, inter-vehicle gaps, and sizes can be abstracted to a single dynamic cohort length L. The lead vehicle distance d_1 to the traffic light is used as the Cohort distance D to the light. The lead vehicle target speed V_t is now orchestrating the entire cohort operation, resulting in an achieved cohort speed V_c. The controller shall learn from the internal dynamic behavior of L and V_c to compute a new speed target V_t. The learning process requires the use of a significant amount of dynamic scenarios representative of real-world conditions bounded by the global achievable comfortable acceleration A_{min} which depends on the cohort's powertrain and vehicle classes content. While considering both light and heavy-duty CAVs, the following heuristics enable simplification.

- To ensure cohort integrity, *"the lead vehicle shall not accelerate faster than the slowest vehicle in the cohort (A_{min})."*
- For driveability and comfort, *"acceleration ranges shall be limited to 'comfortable' accelerations,"* as opposed to the maximum performance acceleration of a vehicle.
- As the ACC controls for the safe distance between vehicles, we, therefore, consider that *"a uniform maximum deceleration, not exceeding the maximum comfortable deceleration rate of the most stringent vehicle is retained as the cohort comfortable deceleration rate b."*

TABLE 1. Local and cohort variables.

Type (units)	Local and State Variables	Abstraction	Cohort State Variables	Network Topology
Count	Vehicle $1, 2, \ldots, n$	$\Rightarrow$	$L = \sum(l_i + d_{si})$ $i = 1, \ldots, n$ (refer to eq (2) for d_{si})	Sensors (input layer)
Length and Distances (m)	Vehicle Length $l_1, l_2, \ldots, l_n$ Vehicle Gap $d_{s1}, d_{s2}, \ldots, d_{sn}$ Vehicle Minimum Gap $s_{o1}, s_{o2}, \ldots, s_{on}$			
	Distance to Light $d_1, d_2, \ldots, d_n$	$\Rightarrow$	$D = d_1$	
Time (sec)	Time to Green and Red t_g, t_r	None	$T_g = t_g$ $T_r = t_r$	
Acceleration (m/sec^2)	Vehicle Acceleration $a_1, a_2, \ldots, a_n$	see heuristics	$A_{min} = \min(a_1, \ldots, a_n)$	
Speed (m/sec)	Vehicle Speed $v_1, v_2, \ldots, v_n$	$\Rightarrow$	$v_1 = f(V_t)$	Output

III. NEUROEVOLUTION PROCESS DEVELOPMENT

As discussed in the introduction, the authors seek to avoid the over-simplification of the complex system behavior required to implement classical optimal control algorithms. Neuroevolution was shown to be capable of direct learning for a wide variety of applications [10], [11] including multi-objective optimization problems [12]. We also seek to achieve faster than real-time performance with a low computing footprint. These capabilities have been demonstrated and implemented for generalized game playing [13], [14] and swarm robotics [15], [16]. Once the learning is complete, it is by design capable of real-time implementation within the same environment. Challenges arise from ample state/action space, global emergent from diverse local behaviors. This is further exacerbated by the unknowns and uncertainties in the real world. Neuroevolution provides the needed mechanism to develop complex adaptive behavior within noisy environments. The evolution of neural network topology and its learning parameters (weights, bias, activation functions) creates the necessary cognitive association between sensed signals and actuators to maximize the system integrity or survivability.

In our application, the sensory input signals consist of the current cohort speed V_c and the five sensor inputs from Table 1. The neural network only requires one output node, namely the velocity target for the cohort V_t. While this target velocity is fed to the lead vehicle ACC function, it does not overwrite the ACC safety limits. This leads to cohort velocity V_c not always matching the target. Therefore, a strong adaptation of the network to the emerging and stochastic nature of the environment is critical. Two stochastic agent-based simulation environments were set up for training and validation.

A. LEARNING AND VALIDATION ENVIRONMENTS

The "learning" environment simulation was developed to maximize the controller robustness to uncertainty. The simulation is for now limited to a one-lane environment. The traffic flow in the training environment was developed using the Gipps model [17]. The model uses the vehicle size l, minimum safety distance s_o, and the computed safe distance d_s with (2) to maintain a safe gap and speed between vehicles. Gaps and safe velocity v_{safe} are computed by (3) based on the cohort "comfortable" deceleration b with Δt representing the simulation time step.

$$d_s \geq s_o + v\Delta t + \frac{v^2}{2b} - \frac{v_{lead}^2}{2b} \tag{2}$$

TABLE 2. Training scenarios variables.

Monte Carlo Variables	Variation Range	Units
Vehicle Start Velocity: V_c	5 to 21	m/sec
Start Distance from Light: D	100 to 1600	m
Start Cohort Length: L	30 to 280	m
Comfortable Acceleration: A_{min}	0.3 to 1.5	m/sec^2
Time to Green at start: t_g	10 to 80	sec
Time to Red at start: t_r	t_g + 10 to 30	sec

$$v_{safe} = -b\Delta t + \sqrt{b^2\Delta t + v_{lead}^2 + 2b(d_s - s_o)} \tag{3}$$

The validation simulator uses AVL's Multi-Agent simulator, which was developed to represent real-world driving conditions accurately. This multi-agent environment combines an Intelligent Driver Model (IDM) [17], reduced-order powertrain models, and detailed vehicle dynamic simulation. The vehicle and infrastructure-based communication is deterministically synchronized via the use of the AVL Model.CONNECT platform [18]. This simulation platform allows to co-simulate systems deterministically using different solvers and time steps and avoids synchronization errors while modeling appropriate delays and latency across vehicle and communication signals.

B. BASIC NEUROEVOLUTION PROCESS

We minimized training time by implementing a two-steps neuroevolution process. In a first step, donor neural networks' topology were manually selected from a library of predefined neural nets. This step speeds up the evolution process as topology evolution is still a complex and time-intensive task [11]. In the second step, each node's weight, bias, and activation functions were respectively tuned and selected using a Particle Swarm Optimization (PSO) algorithm. This method is preferred to Genetic Algorithms by the author for both convergence speed and solution quality during experimentation. This permits the learning process to take just 10 hours on a 16-cores desktop per neural network candidate. The neural network with the lowest LOF value was selected for validation.

A single "training" traffic light was added to the traffic environment to provide the infrastructure information (T_g, T_r) to the neural network. A uniform Monte Carlo (MC) simulation was used to vary the environment parameters (Table 2) across 1,500 training scenarios similar to the one shown on Fig. 2.

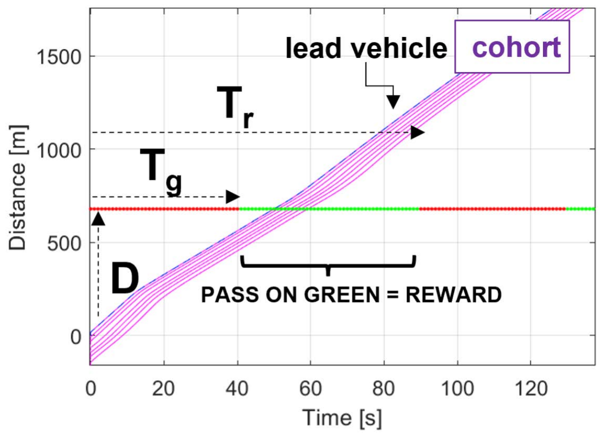

FIGURE 2. Example successful scenario with a eight vehicles cohort (L is around 200m). T_r, T_g and D shown at t = 0s.

Algorithm 1 Neuroevolution With PSO

1: Swarm particles are initialized with random weight, bias, and activation function encoding values.
2: 16 neural networks clone are generated
3: Each neural net is simulated across 1500 scenarios
   a: Training starts after 20 sec to allow the cohort to form
   b: The simulation environment feeds the 6 inputs $[V_c, D, L, T_g, T_r, A_{min}]$ to the input layer
   c: The AI outputs a speed target V_t to the lead vehicle.
   d: The rest of the vehicle follow according to their safe distance limits
   e: Cohort Length and achieved speed is dynamically recomputed
4: Fail/Pass is assessed upon the entire cohort passing the light on green.
5: The LOF value (1) is calculated and drives the next PSO particle iteration (step 2).

The PSO algorithm process is summarized as shown in Algorithm 1. Given that some of the scenarios were not physically achievable (for example, due to the limited acceleration capability of the Class 8 truck), the controller achieved a 60% success on training.

While the neural net provides the lead cohort vehicle with a speed target, its faster than real-time computation speed enables several additional features. Within less than one millisecond, it outputs a 200s long predicted speed e-Horizon based on the current conditions a time t. This is achieved by concurrently running the Gipps model in the loop with the neural network. This information serves as an e-Horizon to the cohort's hybrid vehicle(s) with adaptive powertrain control (PrEM), hence supporting the calibration on the fly of their powertrain and ensuring local energy reduction optimality. This speed profile is also integrated into a predicted cohort position profile to assess the viability of the current strategy in successfully passing the current "green window." This is achieved by comparing the time of arrival at the light ($D = 0$) with T_g and T_r. If the assessment simulation result leads to an unfeasible solution, the next green window information (incrementing T_g and T_r values by the traffic light period) is requested and fed to the neural network input layer. The speed of the neural net was further elicited in generating several speed profiles for different cohort design scenarios. For example, the cohort length L can be varied until a feasible solution is reached if the current conditions were deemed unfeasible. This information can be used to split the cohort. These added-value features form complete Neuroevolution based cohort management (Fig. 3).

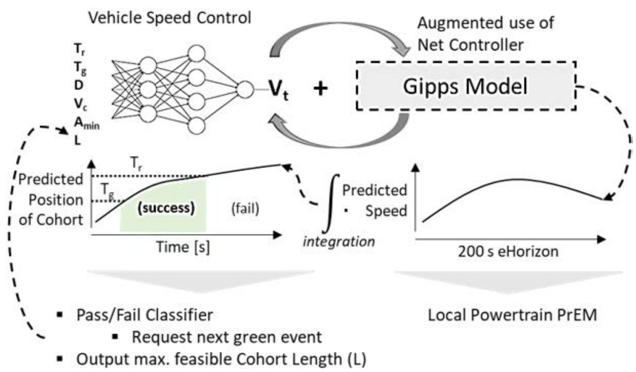

FIGURE 3. Cohort management with its core neural net and added value feature such as eHorizon generation and pass/fail classification.

C. ADVANCED NEUROEVOLUTION PROCESS

With a large number of activation functions available, the PSO process is likely to converge to a local optima. A first step was therefore added prior to the basic neuroevolution process described above. The preselection of the activation function for each neural network node is achieved via using a Weight Agnostic neural network (WANN) step as described in [19]. The network weight are kept uniform across the neural network during each activation function allocation iteration driven by a Latin Hypercube design of experiment matrix. This matrix contains an optimal permutation of 4 activation function for simplicity (ReLu (poslin), Linear (purelin), Radial Basis (radbas) and hyperbolic tangent sigmoid (tansig)). Weight were varied between -1 and 1. For each generated neural network, 1,500 learning simulations are run and the LOF is recorded. The LOF statistics are plotted in (Fig. 4). The lowest mean of the LOF (minimization) for each node is used as the selection for its activation function. Re-running the basic neuroevolution process with these pre-allocated activation functions generated a more robust and higher performing controller (Fig. 5). Note that this controller was not used in the embedded vehicle controller so as to retain the ReLu's computing efficiency.

IV. VALIDATION RESULTS

We present several validation result sets, firstly using the learning simulation environment with a P3 powertrain, secondly using AVL simulation with multiple powertrain models and real world results on a close loop track at ACM.

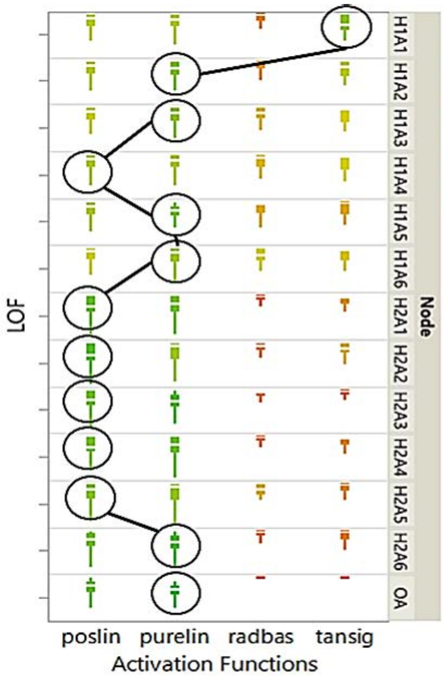

FIGURE 4. Activation function allocation identification (chosen by the lowest box plot mean LOF) for each node of the last 2 hidden (HA) and output layers (OA) via WANN. Note that the radial basis function did not provide added benefits in this case.

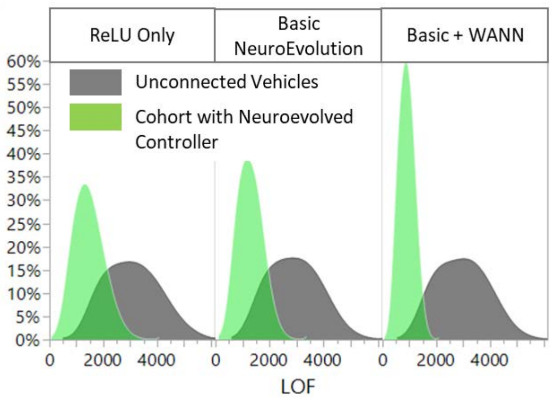

FIGURE 5. LOF value distribution across 1,500 scenarios, comparing unconnected vehicles (Gipps alone) and CAV Cohort with the Neuroevolved controller. The LOF minimization shows higher performance and robustness with the added WANN step compared the ReLu only neural net evolution (ReLU) and the basic PSO Neuroevolution processes. The two-steps approach proves more effective than having the PSO also handling the activation function search.

A. LOF VALIDATION USING A P3 HEV MODEL WITHIN THE LEARNING ENVIRONMENT

A validated quasi-static P3 powertrain was integrated to the Gipps based learning environment. Five thousand scenarios, with various cohort size, were simulated across multi-light networks with varying phasing, timing and speed limits (Fig. 6). The MPG of the unconnected vehicles and corresponding CAV cohort were recorded. The neuroevolved controller shows an average fuel economy benefit averaging 30%, especially when enabling the cohort to split when unfavorable scenarios are detected. Additionally, it confirms

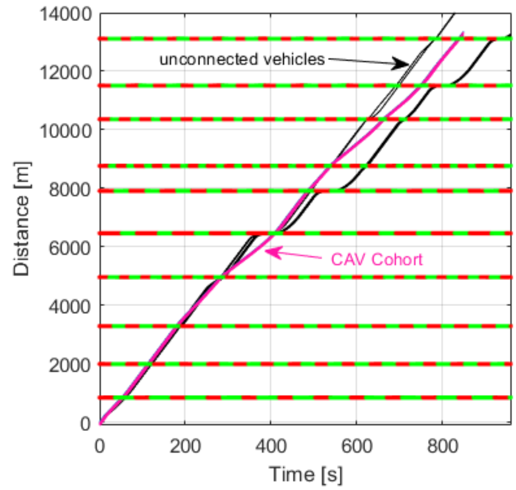

FIGURE 6. Example scenario with 6 vehicles and 10 traffic lights. The CAV cohort with the neuroevolved controller manages to stay formed, and does not need to stop at any of the red lights. The unconnected vehicles encounter several stops and split into distinct groupings.

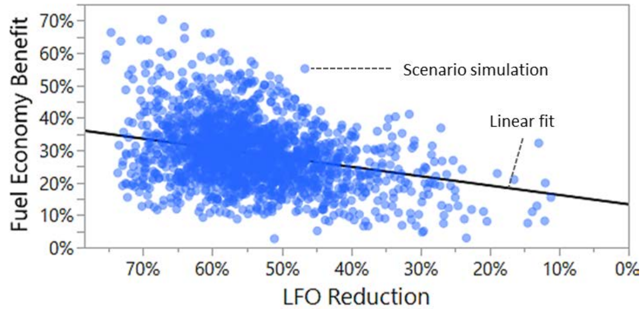

FIGURE 7. MPG benefit for a P3 HEV powertrain fitted wit the connected neuroevolved controller vs. the optimization LOF value over 2,000 validation scenarios. This demonstrates the direct correlation between minimizing acceleration and deceleration events, and the HEV fuel economy performance improvement when operating as a CAV cohort.

that LOF strongly correlates to fuel economy increase, hence validating the assumption that minimizing speed fluctuation is a main driver for energy usage reduction in city conditions (Fig. 7).

B. EDGE CASES VALIDATION WITHIN THE AVL SIMULATION ENVIRONMENT

In this simulation environment, the controller is now submitted to realistic vehicle dynamics. An edge cases scenario is presented here, with a cohort including seven different vehicle types, including a Class 8 vehicle. Noticeably, the Class 8 dynamics during gear shift caused slower than anticipated acceleration rates (compared to the A_{min} range during learning). This compromised the cohort integrity in allowing all the vehicles to pass during one green window. The pass/fail classifier value became evident in allowing the cohort to split appropriately when the cohort integrity became an issue. With this feature each vehicle consistently achieved a positive energy efficiency improvement (Fig. 8). The Sedan PHEV reached 40% in energy consumption reduction in the

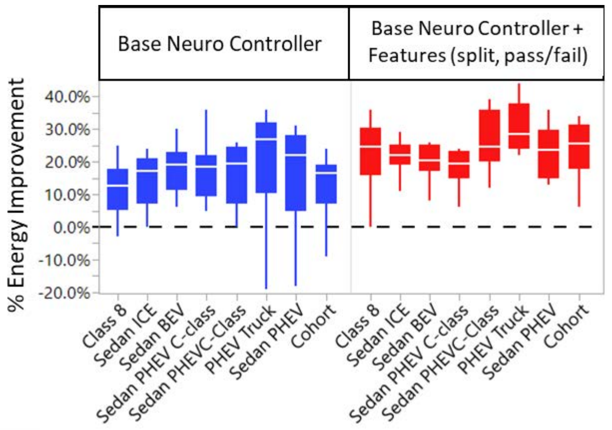

FIGURE 8. Heterogeneous cohort performance box plot statistics across 30 scenarios. On the right, the performance improve with the integration of the pass/fail classification feature, enabling cohort to split when necessary and hence hindering a complete cohort to stop at a red light.

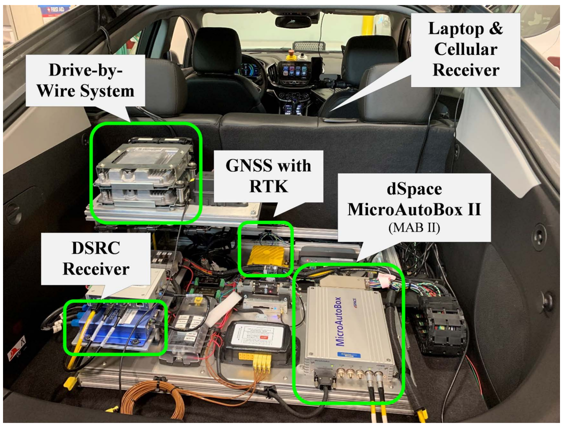

FIGURE 9. Neuroevolution controller integration into the AV stack.

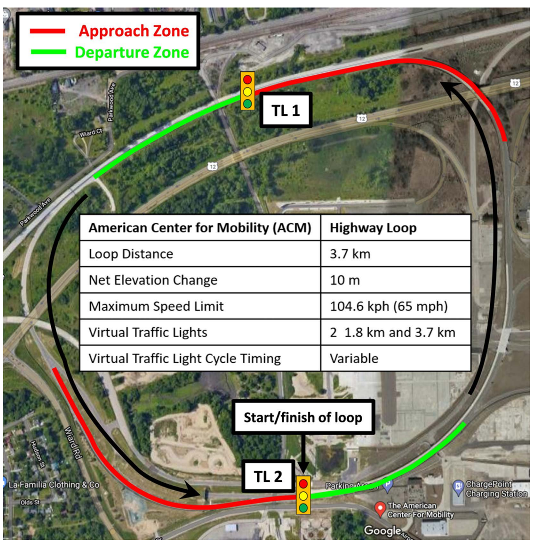

FIGURE 10. Two miles route at ACM with the location of the virtual traffic lights provided by traffic technology services (TTS).

best-case scenario, while a minimum of 5% improvement at the cohort level is ensured.

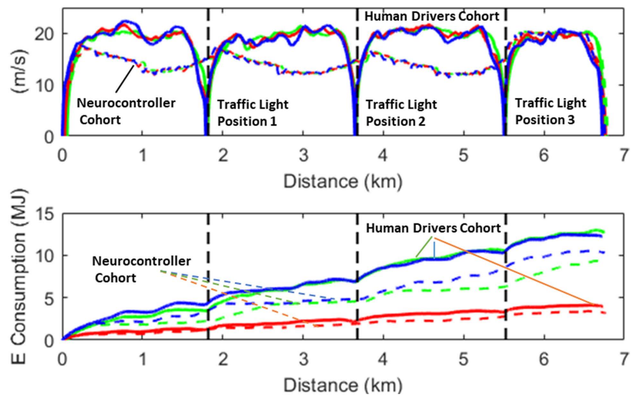

FIGURE 11. Example speed and energy traces during road testing. The human and neurocontroller driven cohorts are in bold and dashed lines respectively. Note the absence of stop time for the optimized cohort. The cohort order here is: GM Volt 1, GM Bolt, GM Volt 2.

TABLE 3. Individual and cohort level energy and time saving during close loop track testing at ACM using random traffic light phasing and timing.

	Speed Limit (mph)	Total Distance (km)	3 Vehicles Cohort	Energy Saved %	Cohort Energy Saved %	Travel Time Saved %
Test 1	45	6.70	Volt PHEV	29%	22.0%	0.4%
		6.70	Bolt	20%		
		6.72	Volt PHEV	16%		
Test 2	45	6.65	Bolt	16%	7.4	1.2%
		6.67	Volt PHEV	12%		
		6.70	Volt PHEV	0%		
Test 3	45	6.65	Bolt	16%	7.3	0.5%
		6.67	Volt PHEV	7%		
		6.69	Volt PHEV	4%		

C. VALIDATION ON CLOSE LOOP TEST TRACK AT ACM

The controller was implemented on Gen II Chevrolet Volt and Bolt up-fitted with a Drive-By-Wire system. The cars are also equipped with a dSpace MicroAutoBox II (MAB II) which functions as an onboard processing unit. The MAB II is used to interface with the Drive-By-Wire system, vehicle CAN channels, and various instruments and can also act as an on-board computer to run specific programs and algorithms defined by the user. The Neuroevolution controller was compiled into C code from Simulink and loaded onto the MAB II (Fig. 9). The controller optimal target speed is sent via CAN to the Drive-By-Wire system, which has its own controller and calibration tables to decide on the required Throttle and Brake Pedal position to achieve the demanded vehicle speed.

The system was tested at ACM. A two miles route (Fig. 10), with two randomly timed and phased connected traffic lights, was driven ten times with and without the neuroevolution controller. A 12% energy reduction was achieve with a cohort of 3 PHEV vehicles, with a lower trip time of 8% compared to normal autonomous operation on a 55 MPH speed limit scenario (Fig. 11). More recent testing at ACM from July 2022 provided the results shown in Table 3. The vehicle order was varied as well as traffic light phasing and timing. Lower benefit from the following vehicles was associated by the vehicle's ACC imperfect behavior in keeping gap and speed steady behind the lead vehicle. In each case, the lead vehicle achieves 16% to 29% energy reduction. Test data also demonstrated that when signal latency was present, the

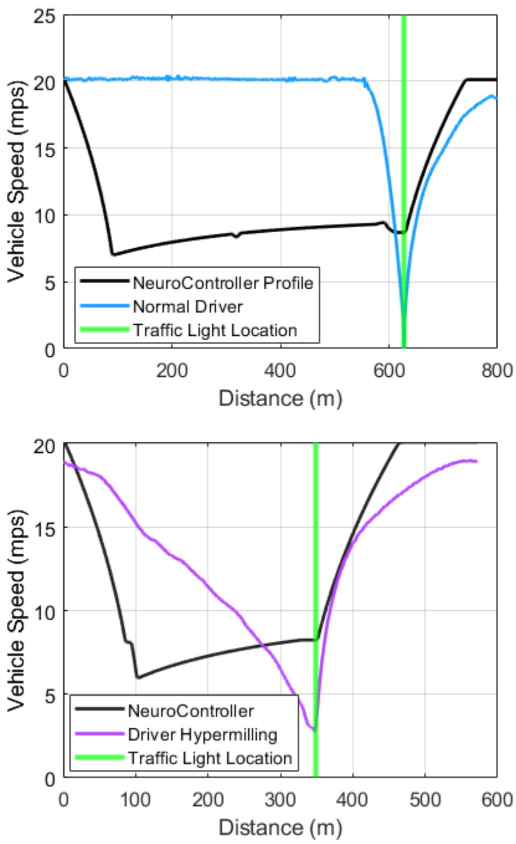

FIGURE 12. Velocity profiles difference between the Neuroevolved controller and a driver without (top in blue) or with (bottom in purple) knowledge of time to green. In the first case, an energy benefit of 38.5% is recorded. This benefit decreases to 5% in the second case.

neuroevolved controller was able to recover by targeting a higher speed target for example once its input layer was finally updated with new values.

Another interesting experiment was preformed where a driver, provided with the time to green, drove a vehicle in hypermiling mode to achieve best fuel economy on the track. While significantly reducing energy usage, the neuroevolved controlled still beat the driver by an additional 5% reduction in energy usage (Fig. 12).

V. CONCLUSION

Neuroevolution provides an effective mechanism to infer self-adaptive optimal control strategies and hence offers a mechanism to ensure sustained optimality. Its development and implementation are simpler and faster than classical optimal control methods. Neuroevolution can be applied to any "black box" system or SoS without reducing the agent behavior or training environment fidelity. The resulting controller far exceeds real-time implementation requirements, enabling it to embed additional features such as e-Horizon predictions and pass/fail assessment on the vehicle. The resulting cohort speed control proved effective and robust to a wide variety of simulated as well as real-world driving conditions, including when signal latency increased at time on the closed loop track. Significant global energy reduction was achieved with cohorts made of highly heterogeneous vehicles as well, which demonstrated the robustness of the chosen objective function. Successful integration in the autonomous system was achieved and energy reduction was successfully validated on a closed loop track.

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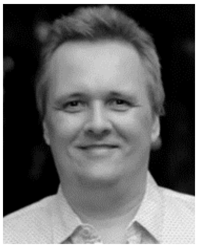

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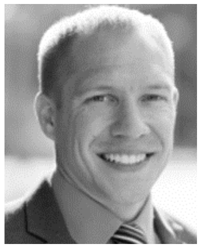

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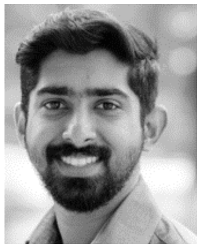

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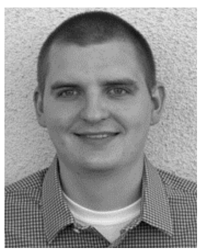

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