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RESEARCH ARTICLE

Predictive Energy Management of Mild-Hybrid Truck Platoon Using Agent-Based Multi-Objective Optimization

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ABSTRACT The objective of this paper is to formulate and analyze the benefits of a predictive non-linear multi objective optimization method for a platoon of mild-hybrid line haul trucks. In this study a group of three trucks with hybrid electric powertrain are considered in a platoon formation where each truck has a predictive optimal control to save fuel with out any loss of trip time. While the controller on each truck uses the look ahead knowledge of the entire route in terms of road grade, the overall platoon controller used a multi agent method (Metropolis algorithm) to define coordination between the trucks. While the individual trucks, showed significant improvement in fuel economy when running on predictive mode, the true savings came from the entire platoon and showed promising results in terms of absolute fuel economy without trading off on total trip time. The proposed algorithm also proved to be significantly emission efficient. A platoon of 3 trucks achieved an average of 10% fuel savings while cutting back 13% on engine out NOx emissions for engine off coasting and 9.3% fuel saving with 8% emissions reduction for engine idle coast configuration when compared to non-predictive non-platoon configuration.

INDEX TERMS Dynamic programming, energy optimization, multi-agent optimization, truck platoon.

I. INTRODUCTION

Due to the rapid explosion of automobile technology in the trucking line haul segment, there has been a tremendous need for making trucking sector more fuel efficient, safe and clean. Platooning, predictive control, hybrid systems, externally heated emission devices are a few such principle areas of research. Studies of platooning trucks in literature are largely experimental-based, and not simulation-based. Of the simulation-based platooning truck studies, Siemon et al. simulated Peterbilt 579 trucks in 4 truck platoons at spacing of 30, 50 and 100 ft gaps at 24.6 m/s (55 MPH) with different trailer configurations (box, shipping container, and flatbed trailers) found fuel savings of 2.5% for the lead, 9.5% for the second, 11.5% for the third, and 13% for the fourth truck [1]. The inter-vehicle dynamics, grade and speed effect, and shifting are not considered as there is no true platooning controller used. Johansson et al. simulates two platooning Class 8 Trucks on a 2 km stretch of flat highway, initially traveling at 90 km/hr ultimately slowing to 60 km/hr [2]. Experimental two-truck platooning results have previously demonstrated platoon-averaged fuel savings of 2.7-9.7% in Class 8 trucks traveling at highway speeds [3]. Platoons consisting of three Class 8 trucks operating at steady-state, on flat ground, at 85 KPH (52.8 MPH), with a gap of 6 m (19.7 feet), demonstrated 4-5% fuel savings for the lead truck, 10% for the second following truck, and 14% for the third following truck at an altitude of 1,800 m (6,000 ft) where the air density is 80% of that at sea level [4]. Flat-ground test track experiments of three platooning heavy trucks at 80 km/hr (49.7 MPH) with a gap of 10 m (32.8 feet) showed fuel savings of 4% for the lead truck, 19% for the second truck, and 17% for the third truck. Fuel savings reduced to 1% (lead), 15% (second), and 16% (third) when the gap was increased to 15 m (49.2 feet) [5]. Peloton Technology experimentally

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demonstrated that a production intent platooning controller is capable of saving 7.25% on flat ground [6], [7]. A comparison of predicted fuel savings from platooning in simulation is made to this experimental data. Tsugawa et al. [8] showed that an automated truck platoon of 3 fully-automated trucks driving at 80km/h with a gap of 10m is capable of steady state driving and lane changing. Fuel saving of 14 percent can be achieved on a test track and along the expressway using this feature. Traffic flow has important decision making aspects in truck platooning as discussed by Calvert et al. [9]. As discussed by them truck platooning has significant effects on traffic flow performance. [10], presents truck platooning in autonomous heterogeneous trucks. As per the paper, every autonomous truck should keep following the leader truck's way-points while maintaining a designated distance from the truck ahead. Reference [11], presents a flexible agent-based simulations model to serve as a matchmaking system for truck platooning. In contrast to centralized systems, this matchmaking is done locally among trucks using real-time data. As per [12], platoon formation changes based on the start and end destinations for each truck and is also affected by other road users. This papers investigates how traffic may affect a merging maneuver of two trucks trying to form a platoon and observed that there could be a merge delay of over 10 percent when compared to the ideal case with the absence of traffic. As per [13], the efficiency of platooning is not only dependant on aerodynamic drag but also by the diffusion of platooning technology, the maximum platoon length and the tightness of time windows. The research in this paper shows that these factors can considerably reduce the positive effects of truck platooning. Guo and Wang [14], investigates the problem of speed planning and tracking control of a platoon of trucks on highways. The speed planning algorithm uses average vehicle instead of platoon leader, thus making speed profile more fuel-efficient for platoons with vehicles if different weights and sizes. The vehicle controller is designed considering road slope and heterogeneity of vehicles. Reference [15] proposes a cooperative distributed approach for forming/modifying platoons of trucks based on real time consensus algorithm. This approach when compared with a centralized optimization-based algorithm, proved to be a more general scheme that is able to form platoons even in cases with large initial separation of trucks and is capable of handling complex situations using its capability to form partial platoons. Zhang et al. [16] discussed that most literature only provides scattered pieces of information regarding fuel economy in truck platoons. This paper summarizes the methodologies, the fuel consumption contributing factors, methods to improve platooning rate, and future control strategies to generate fuel-efficient speed profiles for each vehicle driving in a platoon. Reference [17] proposes a two-layer control architecture to safely and fuel-efficiently coordinate the vehicles in the platoon. The layers contain information on road topography and the real-time control of the vehicles using dynamic programming to compute fuel-optimal speed profile and a distributed model predictive control framework for real-time control of vehicles. Kaluva et al. [18] analyses the impact of platooning in urban environments by studying the influence of inter vehicle distance, platoon size and vehicle speed on the drag coefficients of the vehicles in a platoon. This study utilized two vehicle models, a minibus and a passenger car are analysed to characterize the drag coefficients. Muratori et al. [19] statistically analyses a large collection of real-world US truck usage data to estimate the fraction of total miles that are technically suitable for platooning. This paper focuses on estimating "Platoonable" mileage based on overall highway vehicle use and prolonged high-velocity travelling and established that about 65 percent of the total miles driven could be driven in a platoon formation, leading to a 4 percent reduction in total truck fuel consumption. Reference [20] assesses the impact of an eco-driving training program on fuel savings and reduction of CO_2 emissions in a well-designed field trial. This methodology proposed by Wang et al. includes different types of road sections under various traffic conditions and a systematic method to evaluate the overall and specific impacts of eco-driving. this paper offers great insights for policymakers in road transport planning and for drivers when applying eco-driving techniques. Reference [21] explains how a truck driver controls his vehicle with the motive of maintaining a desired velocity while keeping the fuel consumption as low as possible. This is achieved by estimating oncoming operation points of the powertrain and optimal choice of inputs.This information is used as an input in an algorithm for the implementation of a predictive gearshift program and predictive cruise controller. In the paper [22] a novel predictive technology is used to incorporate the cruise set speed along with a gear shift point. The numerical based algorithm used a combination of nonlinear dynamics constraint and objective cost. The mixed integer problem due to the gear choice is solved partially by the outer convexification process. Benefits are shown on real world and artificial routes. Hellström [23] explores how information about future road slopes can be used in a heavy truck with an aim of reducing fuel consumption without increasing total travel time. The longitudinal behavior of the vehicle is controlled by determining accelerator and brake levels and also which gear to engage. Paper [24] presents a novel predictive control scheme is used for energy management in hybrid trucks driving autonomously on the highway. This scheme uses information from GPS together with speed limits along the planned route to schedule charging and discharging of the battery, the vehicle speed, the gear and decision of when to turn off the engine and drive electrically. Borek et al. [25] presents an optimal strategy for heavy-duty trucks that minimizes fuel consumption in urban ares. This strategy uses an online convex model predictive control strategy that balances a trade-off between reducing braking effort and tracking optimal velocity. Another implementable

TABLE 1. Summary of literature and novel contribution.

Contribution Summary		
Topics	Literature	Proposed
Predictive Single Control	Matured	-
Multiple Interactive Predictive Controls	Insufficient	Contribution
Multi-agent predictive platooning	Insufficient	Contribution

but challenging solution is to use Model Predictive Control approach. Liu et al. used a similar offline simulation and then used the optimal cruise control speed target in a 2 truck platoon [26]. They used a moving window based simple model predictive control approach to solve the objective cost. This problem is solved in real-time using a nonlinear programming optimizer based on interior-point methods as in [27] and is applied in real-time in the framework of MPC. There are wide range of controls available and a variety of vehicle models but none solved an energy management strategy for a platoon using detailed optimal behavior for multiple states and controls. The primary objective of this work is to find the best strategy in terms of global optimality with all levers interacting together. This kind of setup is not studied so far to the best of the author's knowledge. There are no solution available for a predictive controller trying to control more than 4 levers using a dynamical system with more than 5 states for a 3 truck platoon. In this work an attempt is made to design, implement, analyze and understand the multi-objective optimization based, true global behavior for a mild hybrid electric class-8 truck and then extend the optimality to solve a problem for the 3 truck platoon. While the single truck optimality help understand the true optimal strategies than can be deployed on a mild hybrid truck based on look ahead knowledge of the route, the multi-agent based method will define the optimal strategy for a platoon of 3 trucks when look ahead information is available.

Table 1 summarizes the novel contribution made through this work. This research was done as part of bridging the gap between existing literature and what the author thinks shall help design predictive platooning system of class-8 trucks.

II. 1D LONGITUDINAL VEHICLE DYNAMICS

A 1-D longitudinal forward torque model for a 48V mild hybrid configuration in a line haul application is used in this work. Lumped losses are assumed for each components while transferring torque. This is a fair assumption as the objective is to prove the benefits of predictive control in coordinated platooning and should be applicable to any configuration. Subsections below discusses briefly each component.

A. INTERNAL COMBUSTION ENGINE

The engine is of a 15L diesel family which has a power rating of 298-373 kW and a torque rating of 1966-2508 N.m. The fuel map is made up manually to mimic an engine efficiency 47%, as shown in Figure 1. In the figure EM is electric

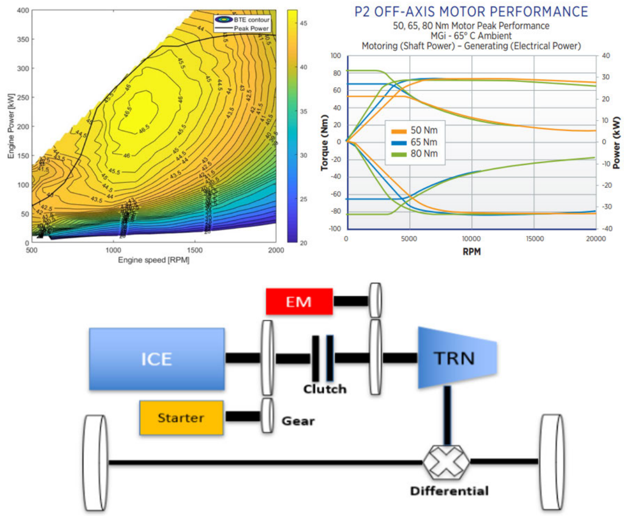

FIGURE 1. Powertrain design [28], [29].

machine, ICE is Internal Combustion Engine and TRN is transmission. It is a 6 cylinder inline configured system [28].

B. ELECTRIFICATION SYSTEM

The electrification system in this configuration consists of a motor generator and an energy storage device. Since the chosen configuration is a mild 48V hybrid system the Motor of choice is a Borgwarner P2 Off Axis motor which supports a torque range up to 80 N.m. Figure 1 shows the torque and power characteristics of the chosen motor as a function if its speed in RPM. It is worth noting that beyond 4000 RPM the torque starts decreasing and power is flattened. The continuous power of the machine used is 15kW with peak torque raging between 50-80Nm.

There are several choices for a 48V energy storage system. In this work a simple configuration from A123 Systems is selected [30]. The battery is moderately sized with 8Ah capacity and a nominal operating temperature of 25C. At this settings it can provide continuous power of 15kW. A simple thermal model for the battery is designed to model the heat loss by the battery. An active cooling system is also in place to increase the rate of heat loss by the battery. Since the battery is small and limited by power, proper heat management of the battery is necessary to utilize its full range of power capability. It is also worth mentioning that the battery is considered to always provide continuous power.

The State of Charge (SOC) is estimated using coulomb counting method [31], [32], [33] which is very efficient and simple way to calculate SOC.

$$SOC(s) = SOC(s-1) + \frac{1}{v(s)} \frac{I_c(s)}{Q_n} \Delta s \tag{1}$$

It is worth to note here that the SOC state is divided by the vehicle speed. This is done to reformulate all vehicle dynamics in distance domain. This change from time domain

TABLE 2. Vehicle parameters [35].

Parameter	Symbol	Value
Vehicle Mass	m	29483 Kgs
Effective mass in cruise gear	m_e	29485 Kgs
Wheel Radius	R_w	0.5m
Aerodynamic drag coefficient	$c_d A_f$	5
Rolling resistance coefficient	c_r	0.005
Air Density	ρ_a	$1.184 kg/m^3$
Gravitional acceleration	g	$9.81 m/s^2$
Engine Maximum Power	$P_{E_{max}}$	$325kW$

is necessary to solve the problem for an independent time solution. This fact will be discussed further in the problem formulation section.

C. TRANSMISSION SYSTEM

The transmission system is a 12 speed overdrive system. There are 12 forward ratios and 2 reverse ratios. Only the top 4 gear ratios are used in this work since the velocity profile used is taken from highway drive. The top 4 gear ratios used are [0.776, 1, 1.3, 1.7] EATON© [34]. It can support a maximum Gross Vehicle Weight (GVW) of 49895 Kg and supports a maximum torque of 2508 N.m. The shift points for the transmission is made up using vehicle speed reference. The way it is derived as a function of vehicle speed and operator throttle so that at cruising speed the transmission stays at top gear. It is also done in a way to keep the engine speed within the best operable BTE region.

D. DRIVE LINE & CHASSIS

The chassis is from a typical line-haul application. A Gross Vehicle Weight (GVW) of 29485 kgs [35] is used in this study which fits nicely into the component requirements as well as a standard load carrying measure. The number of wheels are 18.

A rear axle ratio of 2.64 is used which gives a lot of low end torque propagation at startup and also does not let the engine operating point go, too high at top gear. The optimization result is strongly coupled to these chosen components. Specifically the chassis components are key players in deciding the vehicle dynamics and optimal fuel numbers since they impact the vehicle speed directly. Table 2 shows the base vehicle parameters which are used in the simulation.

E. FORCE BALANCE

The different forces at the wheel is summed up and then divided by the equivalent vehicle mass to get the acceleration. Finally the acceleration is integrated to get the velocity of the vehicle which is used to feed back to the upstream controllers for a full closed loop dynamics. Figure 2 shows the visual of the different forces working on the vehicle on a grade. It highlights the relation between road grade and how it affects various force components in the vehicle along with their direction. The gravitational force as a function of the

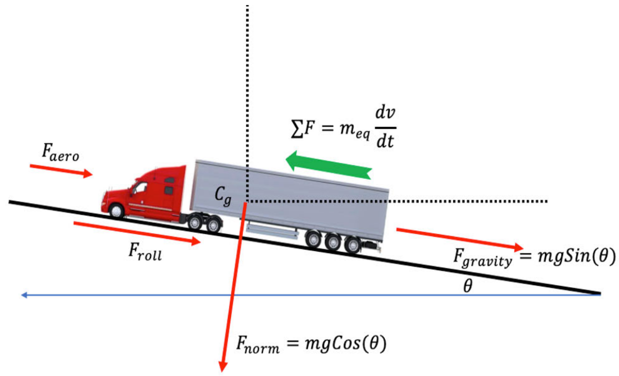

FIGURE 2. 1-D Longitudinal forces on a vehicle.

road grade is given by equation 2.

$$F_{drag} = m * g * sin(\theta) \quad (2)$$

where, θ is the road grade in *radians*

The aerodynamic drag is a direct function of vehicle speed and is given by equation 3

$$F_{aero} = \frac{1}{2}\rho * A_f * C_d * v^2 \quad (3)$$

where, A_f is the vehicle frontal area, C_d is the Drag Coefficient & ρ is the air density.

The road normal force is a function of road grade and is given by equation 4

$$F_{norm} = m * g * cos(\theta) \quad (4)$$

where, θ is the road grade in radians

Hence, using the force balance principle and rearranging, the vehicle speed is given by equation 5

$$v = \int \frac{1}{m}[F_{tractive} - F_{drag} - F_{aero} - F_{norm}]dt \quad (5)$$

The optimal problem is solved in distance domain since the time in this solution is not fixed. Depending on the speed modulation the time for the entire route will change and hence the problem is changed from a fixed time problem to a fixed distance problem. Hence we convert equation 5 as

$$v = \sqrt{(}2 * \int \frac{1}{m * v(s)}[F_{tractive} - F_{drag} - F_{aero} - F_{norm}]ds) \quad (6)$$

where, the initial condition of the integration is Equation 6

$$v_{0s} = \frac{1}{2}{v_{0t}}^2 \quad (7)$$

The initial condition too has to be converted to distance domain since the problem is being solved with time as an independent variable. This is due to the fact that modulating speed will change the time taken to complete the trip and hence total trip time is considered as a factor in the cost objective. The problem is also solved when the truck is active cruise mode at highway speed. Hence an initial condition for the speed is needed. Thus this speed is converted to distance domain using the same analogy as the original force balance equation. It is worth noting here that equation 6 makes vehicle speed a state of the system dynamics. The assumptions made throughout this section while designing the system dynamics are

- Rotational Compliance & Coupling Dynamics between components are not considered for the purpose of this research.
- Losses are considered constant instead of a function of any dependent variables.
- Map based logic is used in every calculation possible to eliminate the need of complex analytical design.

Since the research is based on energy level analysis the above considerations are justified.

Hence the 5 continuous states are Vehicle Speed, Vehicle Position, Engine Fuel Quantity, Battery SOC & Battery Temperature. There is also another state which is the gear number but this is a discrete integer type state hence making the problem suitable for a mixed integer type non-linear problem. The control inputs are Engine Throttle, Clutch Command, Brake Command, & Gear Shift Request.

Power split between the Internal Combustion Engine and Electrical Energy Storage is decided by a supervisory controller. The controller processes the driver demand torque request and uses a state machine to select a power mode out of 4 different modes, namely power split mode, generator mode, engine only mode, and electric only mode. Due to the small form factor for the hybrid system electric only mode is very rarely encountered. The supervisory controller uses full battery power and then commands the remaining power from the engine, in response to driver's demand. Similarly in generator mode, during regeneration the battery absorbs energy to its SOC based limits and the rest is used as motoring torque which slows the vehicle by engine braking.

III. PROBLEM FORMULATION & APPROACH

The problem is complex enough to be solved in a straight forward way. Hence the problem is solved in a two step method. First the predictive problem for the mixed integer non-linear multi-objective problem is solved for a single truck using the look ahead road grade knowledge. We call this the offline solver which is designed to solve the optimal problem for the single vehicle. This solver can run either in a cloud or at a high performing edge device in the vehicle. The optimal output of this controller is fed to the agent based controller which we call teh online controller to distributively control the 3 trucks in the platoon. The offline controller is solved by the author's and is published separately [36]. Equation 8, shows the cost function for the offline controller.

$$\min_{\forall u^* \in \mathcal{U}} \sum [\frac{\alpha}{\omega_{fc}}(\frac{\dot{m}_f(u)}{\mathcal{V}_s(u)}) + \frac{1-\alpha}{\omega_{tt}}(\frac{1}{\mathcal{V}_s(u)}) + \frac{\beta}{\omega_{bt}}(\frac{\dot{T}_{batt}(u)}{\mathcal{V}_s(u)})]\Delta x \tag{8}$$

where, $\dot{m}_f$ is the fuel rate, V_s is the vehicle speed, α is the tuning coefficients for fuel consumed and trip time, ω_{fc} & ω_{tt} are normalizing weights to transform the units in the same domain and Δx is the integration step in distance domain. $\dot{T}_{batt}$ is the rate of change of battery internal temperature and β is the independent tuning weight.

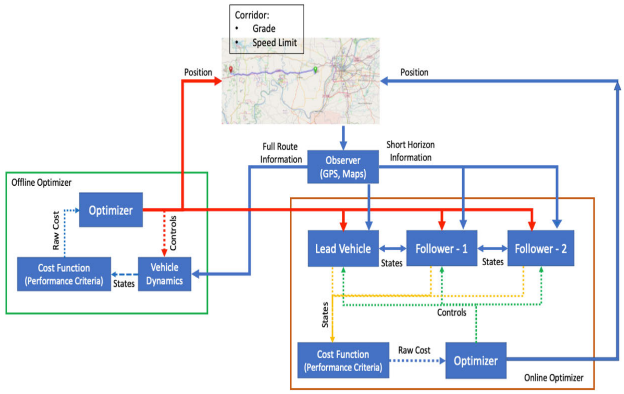

FIGURE 3. Overview of the 2 stage problem hierarchy - single vehicle and platoon.

The dynamics in time domain is converted to distance domain by dividing the differential equations by Vehicle Speed ($v(s)$). Inclusion of time in the cost function is a measure of drivability. It is not acceptable to achieve a fuel efficient solution if the time constraints are not met. In other words the vehicle cannot take more time to cover the route, to save fuel and emissions.

Figure 3, shows the high level architecture of the problem. The look ahead road grade is fetched from the corridor information module, where it is assumed that the full route information is available. The problem has 4 states $x(.)$ = [Vehicle Speed, Transmission Gear Number, Clutch State and Battery SOC], 4 controls $u(s)$ = [Throttle, Clutch Command, Gear Shift Command, Power Split Ratio]. Engine Speed is another derived state which is not explicitly needed by dynamic programming. Position in the route is another exogenous state which is used in the optimal model. Constraints that are modelled in this work are both soft and hard. Vehicle speed is limited between an absolute maximum and minimum threshold as a hard constraint. A soft root mean square type, second order norm constraint is also used which is based on the difference between baseline speed profile and the optimal speed profile. Additional constraints for coast problem is the duration and frequency of coast events. Since the predictive behavior can increase or decrease the vehicle speed from the cruise set speed, it is required to appropriately set the constraints on vehicle speed. Similarly the engine off coast can also increase speed beyond reasonable limits if not monitored correctly. Hence, there are vehicle and engine speed limits set up accordingly while solving the problem. The offline structure and process flow is shown in figure 4

A. ONLINE PLATOON CONTROLLER

The next stage is when the platooning trucks use the optimal control profile. The problem can be solved in multiple ways.

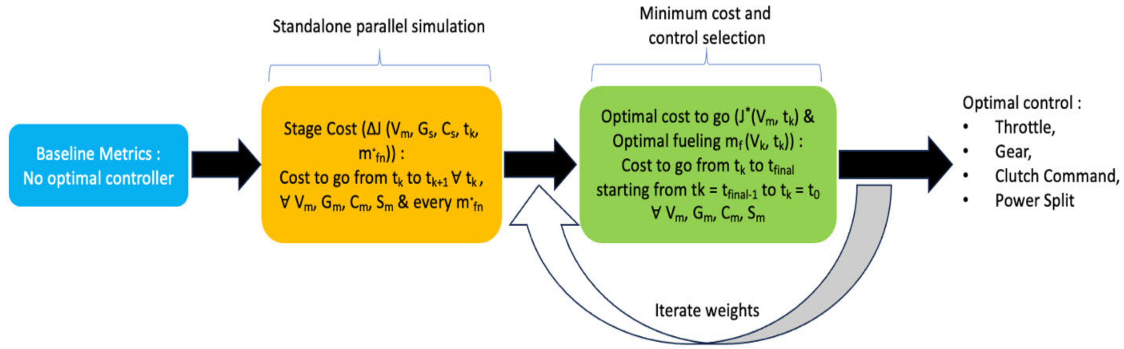

FIGURE 4. Dynamic programming based offline controller structure.

One simple way is to let the lead truck follow the optimal trajectories and the follower trucks passively follow the lead trucks ensuring that the critical distance is maintained. This is typically done using a proportional-integral feed forward controller that tracks the separation distance and adjust brake and throttle power as needed. The other gear and the coast control levers can be applied as it is ensuring dynamical requirements. This is typical to the reactive based control strategy where the lead vehicle drives the entire the platoon mostly. The follower vehicles plays in the throttle and brake space to maintain follow separation distance. while this strategy can be easy to implement it does not guarantee (without validation) whether the results are truly optimal. Later in the section we analyze whether implementing such a strategy is the best tradeoff among all the requirements.

Moving one step further the platoon problem can be solved using traditional optimal control methods such as model predictive control, Mixed integer non-linear program methods, pseudo spectral collocation methods and even Pontryagin's minimum principle. While some of them are used widely in industry for various application and also provides true optimality but it is often challenging if not impossible to implement such algorithms in real time controllers. This led to the requirement of analyzing the global optimal behavior using different methods in this research and understand the over all behavior in terms of optimal results, challenges in implementation, ability to scale up the problem and involving vehicle dynamics.

In this work a simple multi-agent based method is used where each node (trucks) in this case need to be aware of its neighbor's state. The trucks share information about their state variable and are fed with the same global optimal control signals as obtained from the offline problem. The lead and the last truck in the platoon have 1 neighbor each while the middle truck has 2 neighbors. The trucks use a shorter horizon to iterate on the state update values and minimize the cost while meeting the constraints. The state update in this case is for the vehicle speed only and is given by Equation 9 as studied by Boyd et al. [37], [38], where each truck needs to know the separation distance between the trucks from it and then applies the formula to get is updated value.

$$x_i(t+1) = (1 - \sum_{j \in \mathcal{N}_i} \frac{1}{(1+\max(d_i, d_j))})x_i(t) + \sum_{j \in \mathcal{N}_i} \frac{1}{(1+\max(d_i, d_j))} x_j(t) \tag{9}$$

where, N_i is the nodes in the network, $d's$ are the separation distance and $x's$ are the respective states. There are other potential state parameters than can be used for modelling the problem. Battery SOC and battery temperature are two such key parameters. We did not use these two states in modelling the proposed online controller due to the fact that the hybrid system is substantially small compared to the total power requirement of the class 8 application. We have used these states in modelling the reduced order model of the vehicle dynamics but have not used them in the optimal controller. The problem is not solved for optimal SOC points instead the hybrid system is used to provide its maximum power whenever demanded and absorbs all power during regeneration within its motor and battery limit curves.

Figure 5 shows the high level structure of the detailed solution. It has two distinct part running in tandem. The first step is identifying the optimal solution for the single vehicle given the predictive knowledge of the look ahead road grade. This step is achieved by running offline, multi-objective nonlinear mixed integer optimization problem for the single vehicle using dynamic programming [36]. The second step which is the crux of this paper is using the information from the offline controller and run the online version of the real time solver using coordinated consensus algorithm as discussed in teh later sections.

B. DISTRIBUTED AVERAGING BASED CONSENSUS

Multi-agent systems (MASs) have gained wide attention in recent years due to its multi-faceted practical applications, especially in wireless sensor networks, formation control in robots, transportation network optimization, vehicle ecosystem development, etc. In networks of agents (or dynamic systems), "consensus" means to reach an agreement

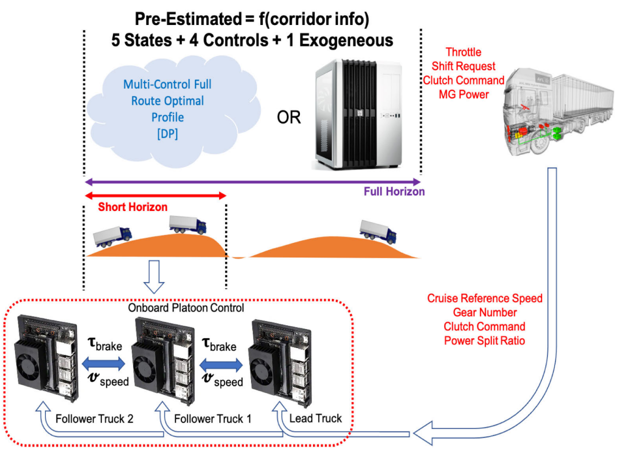

FIGURE 5. High level overview of the full control formulation and hierarchy of the process. The full horizon is used to conclude the optimality for the single vehicle. A short horizon is used to achieve cooperative consensus among the platooning trucks.

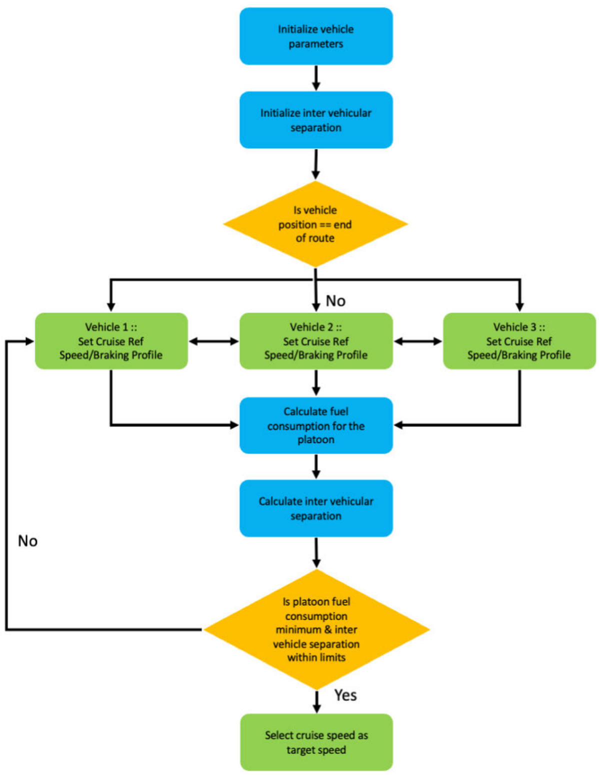

FIGURE 6. Flowchart of the multi-agent based consensus algorithm used in the current problem with 3 vehicles running in platoon.

regarding a certain quantity of interest that depends on the state of all agents. A ''consensus algorithm'' (or protocol) is an interaction rule that specifies the information exchange between an agent and all of its neighbors on the network. Distributed computation over networks has a tradition in systems and control theory. References [39] and [40] also discusses the distributed computing structure using multi agent modes. Flowchart for the online multi-agent based controller is shown in figure 6

The details of the process are defined in the next section where the problem is mathematically formulated. Once the online objective function is derived the 3 vehicle platoon system is simulated as per the flowchart to select and apply the optimal control for the system.

C. PROBLEM FORMULATION

The objective for the online controller running distributed mode calculations is formulated in Equation 10

$$u^*_{1:N}(s) = \underset{u_{1:N} \in R}{\text{argmin}} \sum_{n=1}^{N} \int_0^s \{ \frac{W_f \alpha \dot{m}_{f_n}}{v_{s_n}} + \frac{W_t(1-\alpha) v_{t_n}}{v_{s_n}} + \tau_{brake_n} \} ds \tag{10}$$

subject to,

$$\dot{x}(s) = f(x(s), u(s), w(s)) \tag{11}$$
$$y(s) = g(x(s), u(s), w(s)) \tag{12}$$
$$\dot{d}_n(s) = v_n(s) - v_{n-1}(s) \tag{13}$$

and, non-linear constraints

$$v_{min} \leq v(s) \leq v_{max} \tag{14}$$
$$\tau_{brk,min} \leq \tau_{brk}(s) \leq \tau_{brk,max} \tag{15}$$
$$d_{min} \leq d(s) \leq d_{max} \tag{16}$$

The cost objective is a summation of fuel consumed and total trip time. Trip time is added to compensate for the excessive slow down of the vehicle in order to save fuel. The other component in the cost function is the braking work. The vehicle will try to brake in order to maintain the safe distance between the trucks. The addition of braking work will make sure that the trucks are not utilizing excessive braking.

The problem is solved by considering each truck as an agent with the other trucks being it's neighbor. Hence the lead truck and the last truck in the platoon has 1 neighbor each while the middle truck has two neighbors. Hence the middle truck has two edges. Only the vehicle speed state in this case is updated using a generalized Metropolis Algorithm [38], [41] and the other control levers are applied as they are from the offline optimal results. If the optimal control violates the constraints then the constraints gets the priority and the truck comes out of the optimal profile. As, an example if the truck cannot be in coast mode in the platoon due to a constraint violation then it comes of coast mode and runs normal operation. In general a consensus process recursively evolves with respect to a discrete time scale. In general for a consensus algorithm, agent i sets the value of its own agreement variable at time $t+1$ based on the average of its current value and the neighbor's value,

$$x_i(t+1) = \frac{1}{(1+d_i)}(x_i(t) + \sum_{j \in \mathcal{N}_i} x_j(t)) \tag{17}$$

where, N_i is the set of indices of agents of $i's$ neighbors and d_i is the number of indices in N_i. Boyd et al. [37], [38] [41] provided a better algorithm called Metropolis Algorithm

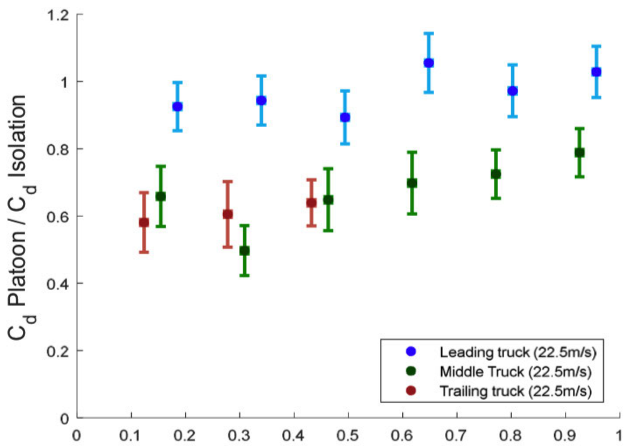

FIGURE 7. Drag coefficient as a function of inter vehicular separation.

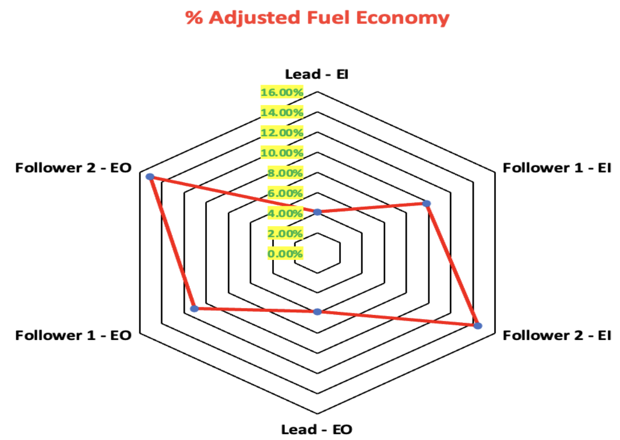

FIGURE 8. % Fuel Economy radar for the 3 platooning trucks - Lead, Follower 1 and Follower 2. The fuel economy radar shows the numbers for both engine coast condition as well as engine off coast conditions.

where each agent needs to know the number of neighbors of each of its neighbors, The state update is given as,

$$x_i(t+1) = (1 - \sum_{j \in \mathcal{N}_i} \frac{1}{(1+\max(d_i, d_j))})x_i(t) + \sum_{j \in \mathcal{N}_i} \frac{1}{(1+\max(d_i, d_j))} x_j(t) \tag{18}$$

We used this algorithm with the vehicle as the state variable which is updated at each time step for the short horizon in real time following the minimum objective cost and constraints. d for the lead and the last truck is 1 and the middle truck is 2 depending on number of edges. The other control levers are not updated based on this algorithm as it will make the problem challenging and it is not expected to get much benefit by doing so.

The optimal speed trajectory for the single vehicle in this route is captured from global offline optimal solution and is fed as the cruise target speed for the individual vehicles in the platoon. The job of the online multi-agent controller [39], [40] is to coordinate with each vehicle in the platoon to follow the set reference speed and maintain a safe inter-vehicular separation using the proposed Metropolis Algorithm. This control is needed because simply feeding the speed target will make the trailing vehicles run faster than the lead vehicles and collide with each other since the trailing vehicles will have less aerodynamic drag and will speed up more. Figure 7 shows the relative change in drag coefficient as a function of vehicle separation [42], [43]

The reduction in Aerodynamic drag coefficient is given in Equation 19 which is the fraction by which the aerodynamic drag coefficient will change based on the separation distance. The constants $C_{D,1}$ and $C_{D,2}$ are adjusted based on polynomial fit from open literature data.

$$\Phi(d_i) = (1 - \frac{C_{D,1}}{C_{D,2} + d_i}) \tag{19}$$

It is worth noting here that the multi-agent controller will run discrete control optimizer in each truck knowing the grade information and complete optimal optimal profile for each truck in the platoon. Each individual agent will try to solve the cost for its own which there by in conjunction with the global optimal input target will achieve best fuel economy for the entire fleet. Additional control levers in this case is the braking effort and the inter vehicular dynamics are also included.

IV. SIMULATION RESULT ANALYSIS

The problem as described above is solved for the 3 trucks in platoon. The separation distance between the trucks are dynamically modified with the intention of spending the least amount of energy as well as maintaining the separation distance. The braking effort is part of the objective function to make sure that the system will not have to brake too often to loose kinetic energy which is a loss at the expense of the fuel energy. In this section the benefits are analyzed and studied. The first Figure 8 is the radar plot of the adjusted Fuel economy of the 3 trucks. There are 2 sets of data in the plot. One is for the coast events when engine is idle and the other for the case with engine off. On an average the 3 truck platoon achieved 9.42% better fuel economy over baseline simulation results. This result is for the engine idle coast event. Similarly for the engine off coast scenario the average went up to 10.65%. The trend in improvement is similar though for both the scenario. The engine off scenario made the lead truck do more better in terms of fuel economy.

Figure 9 shows the key metrics related to fuel consumption and the associated parameters affecting it. It is observed that an average of 9.5% fuel benefit is achieved in the engine idle scenario for the platoon. The engine off case shows an average of 10.7% for the platoon. The plot show 6 sets of bar plots. Each set comprises of 5 key metrics (Green - Adjusted Fuel Economy % Change, Red - Absolute Fuel Economy % Change, Orange - Absolute Trip Time % Change, Yellow - Engine Cycle Work % Reduction, Purple - BTE %

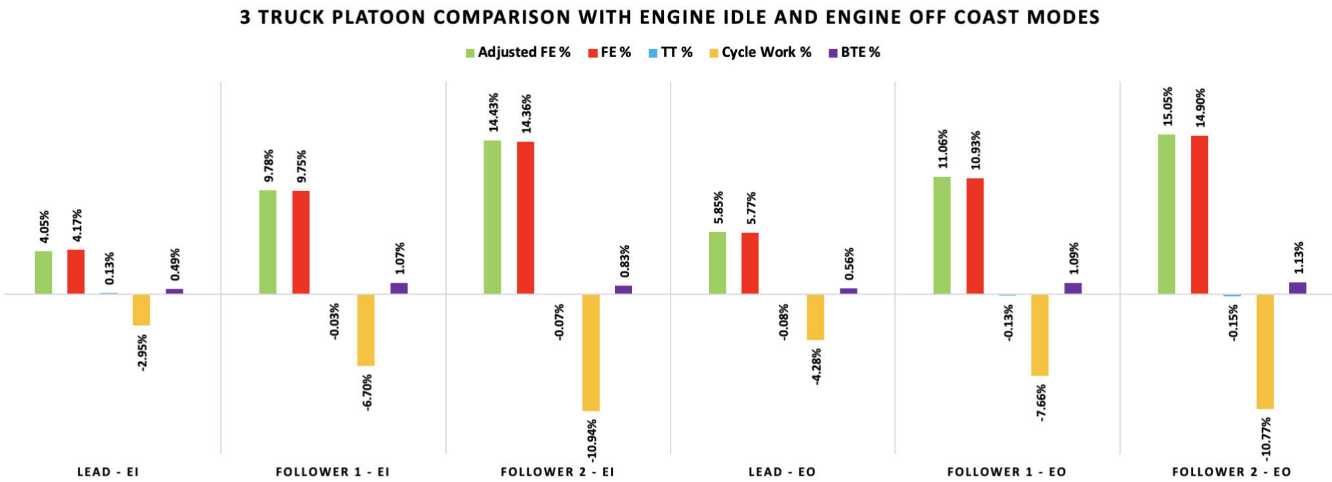

FIGURE 9. Key metrics showing the comparison of benefits along with Cycle work and BTE for the 3 class 8 truck in Platoon with the two distinct cases of engine idle coast and engine off coast.

Change). The 3 sets of bar plots are for engine idle case while the last 3 sets are for the engine off case. The lead vehicles in both the cases shows almost similar behavior to the single vehicle optimality. The associated benefit is a result of cycle work reduction and aerodynamic work reduction. There is almost near similar improvement in brake thermal efficiency in all the cases.

Figure 10 shows the comparison of different negative work reduction metrics. The bar plots in green shows the reduction in aerodynamic drag work. The reduction of the lead trucks in both the Engine Idle as well as the Engine Off case is negligible compared to baseline results. This is considering the fact that the lead trucks follow the optimal speed profile almost perfectly. The follower trucks shows more reduction due to the reduction in aerodynamic drag in the following trucks. The reduction is more in the second following truck than the first as expected due to more reduction in aerodynamic drag in the second follower than the first. Engine off case shows a bit more reduction in aerodynamic work loss. Blue bars show the reduction in negative work which includes motoring loss, engine braking along with service braking. The follower trucks in both engine idle as well engine off scenario shows less reduction due to the application of more service brakes in order to maintain safe operable distance between the trucks. Engine idle scenario shows less reduction in negative work than the engine off case. Figure 11 shows the detailed time series plots of the 3 trucks in platoon as a function of vehicle position in x-axis. The trucks show dynamically varying separation distance with the trailing truck almost going 120m during heavy hills. This can pose challenge with cut-ins. This was because of a coast event before a hill. This large separation distance also reduce the benefits associated with aerodynamic drag reduction. This is an anomaly observed in the solution space. This can be better tuned by making the separation constraint more stringent. The battery SOC is pretty much dependent on the reactive grade profile. It is also observed that the wheel braking increased a lot. This is also shown in Figure 10. The blue bar plots in this figure shows significant less reduction in the negative work which is due to the fact that wheel braking has increased. Figure 12 shows the data for the coast events and % time in coast for the system of trucks in platoon. The plot depicts 2 sets of data one with the engine idle coast scenario and the other for the engine off coast. It is noted that for the following trucks the total number as well as the total time in coast is significantly lower than the lead truck. This behavior is similar to both the engine idle and engine off coast case. This is analytically because of the speed modulation in the follower trucks which made the trucks go out of coast in most of the cases or not get into coast at all. In both the case it is observed that the BTE improves progressively with increase in Fuel Economy. In the Engine Idle case the BTE change reduced a bit for the last truck in the platoon but still it shows better fuel economy. The benefits associated here is more contributed by the reduction in aerodynamic drag reduction. The BTE did not improve a lot because of more gear shifts with the predictive knowledge as well as to maintain separation distance.

Figure 13 is another nice metrics to analyze and look at. This indicates the fuel benefits associated with overall aerodynamic drag work reduction. The major fuel benefits are definitely due to the reduction in drag coefficients in the following trucks. The work reduction is definitely affecting fuel economy but there are other contributors as well in the benefit such as negative work reduction.

Table3 shows the improvement in Fuel Economy when predictive control is used as compared to non-predictive controls. It shows that on an average for the 3 truck platoon there is an overall net fuel economy improvement of 2.94% for the predictive controls with Engine Idle scenario and 3.99% for the Engine off scenario. Table 4 captures the detailed metrics of the multi-agent based optimal result for the 3 truck in platoon. The results are from the problem

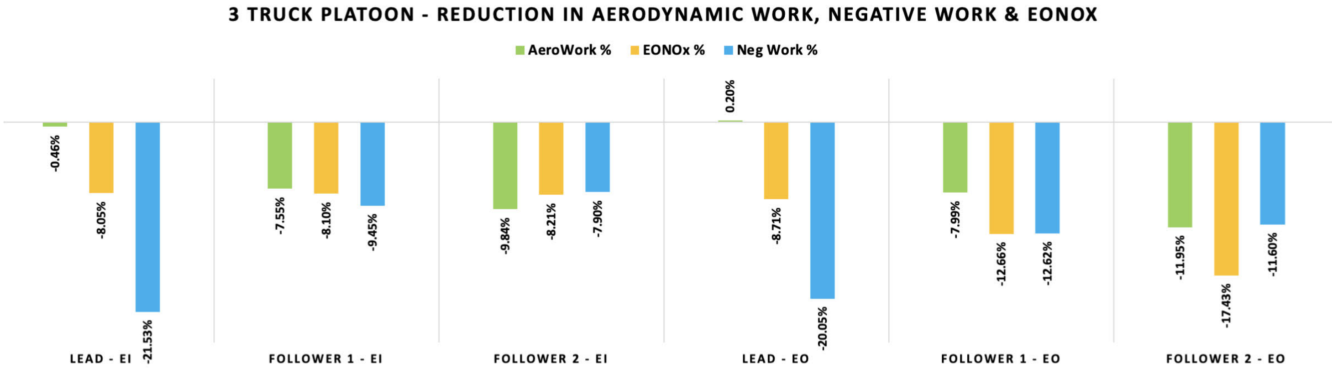

FIGURE 10. Reduction in aerodynamic work along with associated EONOx reduction. The last bar plot shows the reduction in negative work which includes engine braking, motoring losses and service braking.

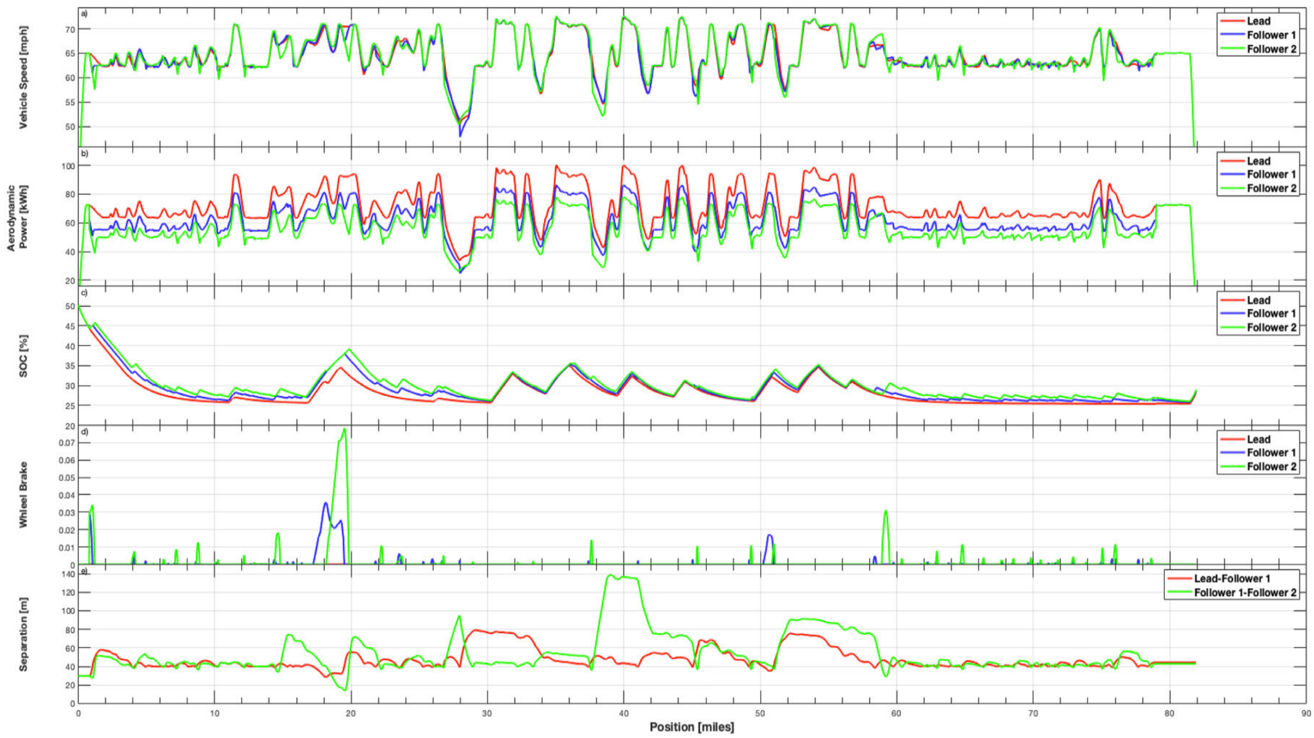

FIGURE 11. Subplot 1 is the Vehicle Speed Trajectory of two trucks in platoon. Subplot 2 is the following distance of the second truck in the platoon. Subplot 3 is the engine out NOx for the lead as well as the follower truck which shows no improvement in NOx reduction by the follower truck.

TABLE 3. Comparison of key metrics between predictive look ahead based optimal control vs. non-predictive controls in the 3 truck platoon system.

	Engine Idle			Engine Off			Non-Predictive	
Metrics	Lead	Follower 1	Follower 2	Lead	Follower 1	Follower 2	Follower 1	Follower 2
Fuel Economy	4.05%	9.78%	14.43%	5.85%	11.06%	15.05%	7.01%	11.88%
Aerodynamic Work	-0.46%	-7.55%	-9.84%	0.20%	-7.99%	-11.95%	-13.34%	-14.83%
Cycle Work	-2.95%	-6.70%	-10.94	-4.28%	-7.66%	-10.77%	-4.24%	-6.84%
BTE	0.49%	1.07%	0.83%	0.56%	1.09%	1.13%	1.11%	1.88%
Negative Work	-21.53%	-9.45%%	-7.90%	-20.05%	-12.62%	-11.60%	0.57%	1.92%
EONOx	-8.05%	-8.10%	-8.21%	-8.71%	-12.66%	-17.43%	-6.36%	-8.55%

with Engine Idle Coast condition. The detailed metrics show the absolute numbers and how they change with different scenarios for the lead and follower trucks.

Table 5 captures the detailed metrics of the multi-agent based optimal result for the 3 truck in platoon. The results are from the Engine Off Coast condition. Results show

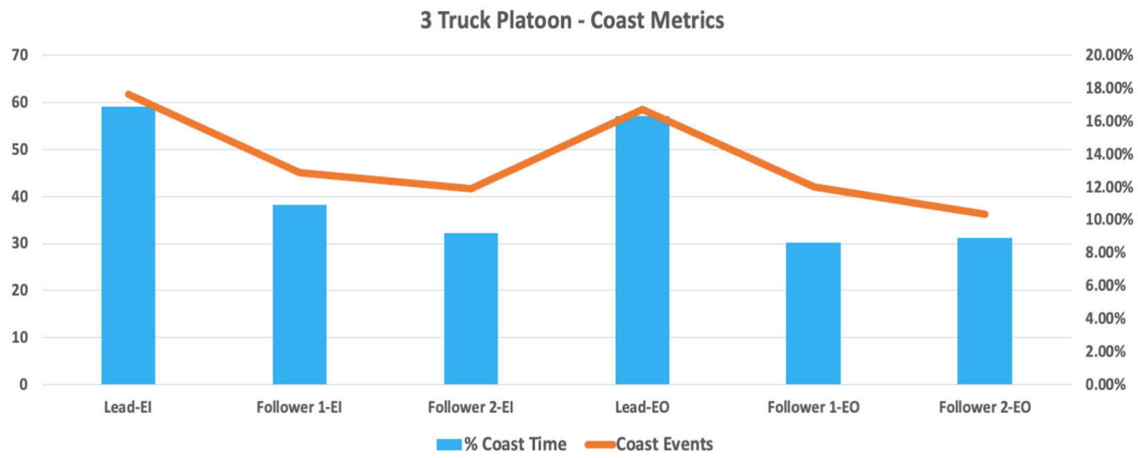

FIGURE 12. Coast metrics for the 3 trucks in platoon - the engine idle and engine off metrics shows clear difference in optimal behavior.

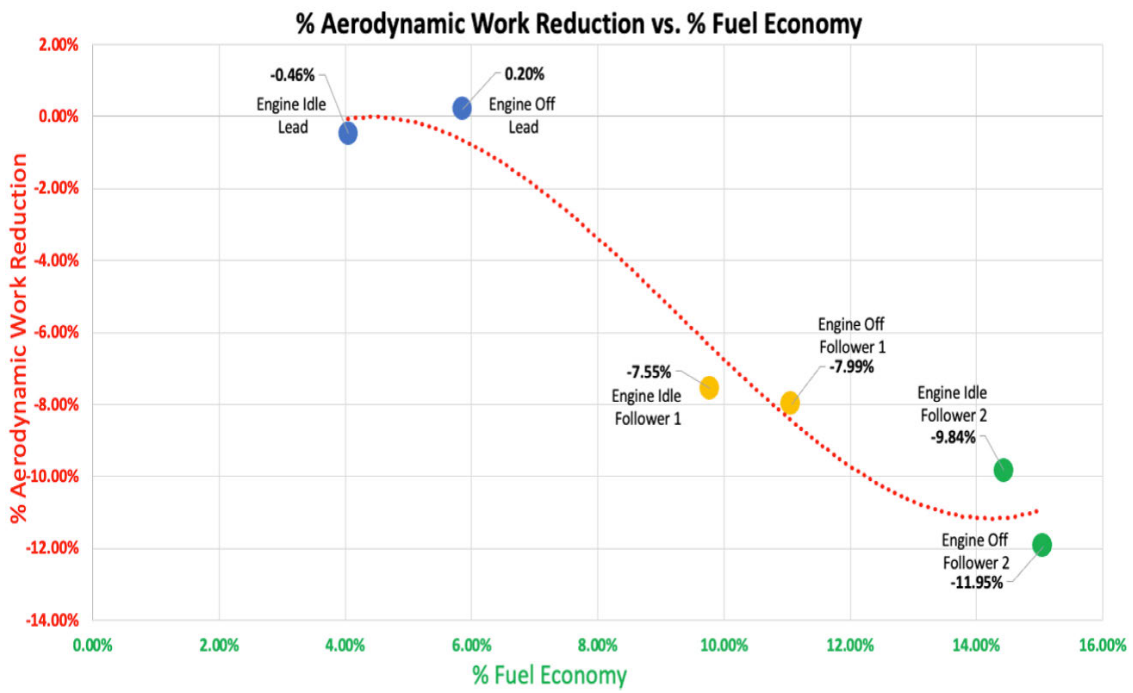

FIGURE 13. % Aerodynamic drag work reduction as function of % Fuel Economy. The % reduction in aerodynamic drag work is calculated based on baseline simulation results.

TABLE 4. 3 Truck platoon metrics running optimal control. All the vehicles have knowledge of the offline optimal control trajectory. The individual trucks are running consensus agent based algorithm to calculate the final optimal path. The metrics shown are with engine idle coast scenario.

		Lead Truck		Follower Truck 1		Follower Truck 2	
Metrics	Units	Absolute value	% change	Absolute value	% change	Absolute value	% change
Fuel Economy	mpg	9.97	4.17	10.5	9.75	10.95	14.36
Trip Time	s	4605.6	0.13	4598.3	-0.03	4596.4	-0.07
Number of Shifts	-	37	-	35	-	36.	-
Cycle Work	kWh	141.77	-2.95	136.3	-6.7	130.1	-10.94
BTE	%	45.27	0.49	45.85	1.07	45.60	0.83
Negative Work.	kWh	-23.25	-21.53	-26.83	-9.45	-27.29	-7.9
Aerodynamic Work	kWh	89.76	-0.46	83.364	-7.55	81.298	-9.84

% change is compared to baseline simulation running rule based SOC control without any predictive knowledge

TABLE 5. 3 Truck platoon metrics running optimal control. All the vehicles have knowledge of the offline optimal control trajectory. The individual trucks are running consensus agent based algorithm to calculate the final optimal path. The metrics shown are with engine idle coast scenario.

		Lead Truck		Follower Truck 1		Follower Truck 2	
Metrics	Units	Absolute value	% change	Absolute value	% change	Absolute value	% change
Fuel Economy	mpg	10.12	5.77	10.62	10.93	11	14.90
Trip Time	s	4596.1	-0.08	4593.8	-0.13	4592.8	-0.15%
Number of Shifts	-	37	-	41	-	40	-
Cycle Work	kWh	139.83	-4.28	134.89	-7.66	130.354	-10.77
BTE	%	45.33	0.56	45.87	1.09	45.91	1.13
Negative Work.	kWh	-23.69	-20.05	-25.89	-12.62	-26.192	-11.6
Aerodynamic Work	kWh	90.356	0.20	82.97	-7.99	79.393	-11.95

% change is compared to baseline simulation running rule based SOC control without any predictive knowledge

that applying predictive road grade knowledge to a set of platooning trucks,

- Adaptive speed modulation can provide additional fuel benefits in platooning trucks on top of savings due to aero drag reduction alone,
- Follower trucks shall not need predictive gear shifts,
- Follower trucks shall save electric energy during heavy grade and use it to supplement longer coast events in the flat section,
- Dynamic separation shall be limited to 20 to 120 meters,

V. CONCLUSION

A multi-objective non-linear mixed integer problem is solved in this paper for a distributive system using a multi-agent based optimal controller. The problem is setup in two stages, one offline and then the results of the offline solution is used in the online multi-agent based controller. The offline controller used a dynamic method based predictive control scheme to find the most optimal operating point of a vehicle given the road grade angle of the entire route is known a-priori. The optimality of the vehicle was attributed to the global optimum of the 4 major control levers in the vehicle which are cruise set speed, coasting, gear shift and power split between the electric machine and the combustion engine.

The next online phase of the controller is to use the optimality condition from the single vehicle and apply it to a platoon of 3 vehicles using a distributed consensus algorithm for multi-agent based systems. The objective was to safely follow the lead vehicle by each vehicle and modulate the offline control inputs so that the platoon system achieves global optimality in terms of saving fuel. Since speed is the key vehicle state parameter is impacted vastly by the reduction of aero-dynamic drag in a platoon, cruise set speed and braking are used as state parameters in the online optimal controller. Other control levers from the offline controller are fed to online controller as it is and those are restricted in operation by the vehicle optimal operating zone. Recalling from the offline global optimal rationale, the coasting, gear shift and power split zone are decided based on optimal engine operating conditions. Hence, in the online controller if the optimal engine operating condition is met then the control levers will not get triggered even if the offline controller has a trigger active. Thus even though the online controller only uses cruise speed as the primary state for optimal cost but the other 3 control levers are implicitly applied to reach global optimality. These control levers can be included in the online optimal solver but the benefits achieved in comparison to computational cost to implement it in a real time controller is not significant. The findings of this study show significant potential for fuel savings along with emissions reduction when predictive knowledge is applied to individual vehicles in a platoon. Though in this work a set of 3 vehicles are used but this methodology can easily be extended to multiple trucks in a platoon system. Future work shall explore the extent of benefits and any potential drawback with platoon network consisting of multiple trucks. This should be done in a sequence by adding more control levers and objectives to the problem. Uncertainty in vehicle operation is also a potential candidate to explore. Adding all these constraints to the problem will help achieve true global optimality of the system but will also challenge the computational limitations to solve the problem real time.

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