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Abstract

Transportation vehicle and network system efficiency can be defined in two ways: 1) reduction of travel times across all the vehicles in the system, and 2) reduction in total energy consumed by all the vehicles in the system. The mechanisms to realize these efficiencies are treated as independent (i.e., vehicle and network domains) and, when combined, they have not been adequately studied to date. This research aims to integrate previously developed and published research on Predictive Optimal Energy Management Strategies (POEMS) and Intelligent Traffic Systems (ITS), to address the need for quantifying improvement in system efficiency resulting from simultaneous vehicle and network optimization. POEMS and ITS are partially independent methods which do not require each other to function but whose individual effectiveness may be affected by the presence of the other. In order to evaluate the system level efficiency improvements, the Mobility Energy Productivity (MEP) metric is used. MEP specifically measures the connectedness of a system while accounting for time and energy externalities of modes that provide mobility in a given location. A SUMO model is developed to reflect real traffic patterns in Fort Collins, Colorado and data is collected by a probe SUMO vehicle which is validated against data collected on a real vehicle driving the same routes through the city. Individual vehicle and system level efficiencies are calculated using SUMO outputs for scenarios which integrate POEMS and ITS independently as well as jointly. Results from application of POEMS and ITS show improvement in energy consumption and travel times respectively when compared to the respective baseline scenarios. Our conclusion is that there are promising synergistic benefits to travel time and energy efficiency when POEMS and ITS are combined.

Introduction

The fuel-based transportation system has a significant impact on human interactions with the environment and our nation's economy. When compared to other modes of transportation such as aircraft, rail, and marine, road-based travel is responsible for the greatest share of CO_2 emissions, greenhouse gas (GHG) emissions, and energy usage. Vehicles transport 11 billion tons of freight and passengers over 3 trillion vehicle-miles annually. The transportation sector accounts for over 30% of total US energy consumption, and the average US household spends more than 15% of total family expenditures on transportation, making it the costliest expense category after housing [1].

Knowing that transportation emissions surged more than emissions from any other sector over the last thirty years, transportation emissions must be a primary focus of mitigation efforts [2, 3]. Employing emerging techniques to minimize the environmental consequences of road-based transportation can thus go a long way into mitigating the entire environmental implications of the transportation industry. Connected and automated vehicle (CAV) technology and electrification are two examples with significant promise to reduce emissions from road-based transport and facilitate decarbonization of the transportation sector. Aside from improvements in powertrain technology, recent automotive sector developments have resulted in considerable advancements in CAV technology and improved vehicle control strategies. Vehicle connectivity and automation are distinct technologies that can exist separately from one another yet have significant synergistic characteristics. The ability of a vehicle to communicate information with other cars and infrastructure is referred to as connectivity. Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and other cooperative communications networks can provide this functionality [4-11]. Vehicle automation refers to any scenario in which management of a vehicle capacity that would typically be monitored by a human driver is transferred to a computer which is referred to as Advanced Driver Assistance System (ADAS). Examples of ADAS are Cruise control, adaptive cruise control, active lane-keep assist, and automated emergency braking that may be found in today's vehicles.

Vehicle electrification is another key component to improve fuel economy and reduce emissions. Hybrid Electric Vehicles (HEV) and Plug-in Hybrid Electric Vehicles (PHEV) have recently received a lot of attention due to their higher potential to improve fuel economy (FE) and emissions compared to traditional Internal Combustion Engine (ICE) vehicles [12]. However, there is still scope for enhancing the performance of the current generation of HEVs [13]. Recent application of CAV technology shows improvement in energy efficiency on HEVs and PHEVs through implementation of Predictive Optimal Energy Management Strategies (POEMSs) [14-19].

POEMS is an application of optimal control where a mathematical optimization problem is formulated by defining the mass of fuel used as a cost to be minimized over a fixed drive cycle [14]. POEMS can be formulated as a real time control using either Pontryagin's Minimum Principle (such as in ECMS [20]) or using Dynamic Programming (DP) over a limited prediction time horizon. The application of DP over a limited prediction time horizon is referred to as Model Predictive Control (MPC). In either case predicted future vehicle velocity is used as an input to the strategy [6, 21]. POEMS performance is, thus, dependent on the quality of future vehicle velocity predictions. In recent years, vehicle connectivity and sensing technologies as well as advances in Machine Learning (ML) and Artificial Neural Network (ANN) technology have made high fidelity predictions feasible [22-25] enabling the implementation of POEMS.

Intelligent technology has become a key solution to traffic control in urban cities to mitigate congestion and reduce vehicle delay. Intelligent traffic signal control efforts primarily focus on applying different algorithms to meet the needs of traffic safety and efficiency with the data from monitoring cameras, road sensors, existence detectors, etc. [26]. Typical modes of operation for traffic signals include pre-timed (fixed time) and actuated operations. Despite being straightforward and easy to coordinate between intersections, pretimed operation is more cost-effective for close intersections with constant traffic volumes but lacks flexibility to adjust with traffic demand and possibly causes excessive vehicle delays. Actuated operation, on the other hand, can adjust phase durations and sequences by detecting real-time traffic conditions, including prolonging or shortening phase durations and skipping a phase based on traffic demand. However, actuated operation does not have a fixed cycle length and is therefore hard to coordinate among intersections.

Traffic signal designs are critical to traffic safety and efficiency at intersections during day-to-day service including normal or heavy traffic scenarios [27]. Significant research efforts have been put forth to study signal timing optimization techniques to mitigate recurring traffic congestions during rush hours. An improved automatic traffic volume detection technique using V2I communication was proposed to get the traffic information in time for the following optimizations [28]. Discrete dynamic optimization models for optimal cycle length and green time allocation were evaluated to identify the most appropriate design to deal with congested traffic scenarios [29]. In recent years, there have been some emerging research efforts investigating intersection signal designs for non-recurrent congestion. A cell transmission model for a signalized intersection was developed for different congestion evacuation schemes [30]. GPS data was utilized for a global network modeling to evaluate the traffic condition with matrix factorization and clustering methods during emergency recovery [31]. A signal timing optimization model using queue length as the penalty value has also been developed under traffic incident scenarios, in which a heuristic algorithm (simulated annealing algorithm) was adopted [32].

With the need to minimize energy and time expended during travel also comes the need to quantify the benefits of doing so in a united and holistic way. The Mobility Energy Productivity (MEP) metric developed by researchers at the National Renewable Energy Laboratory (NREL) measures travel accessibility to opportunities with weightings for travel time, travel cost, and energy use at any given location [33, 34]. MEP has been constructed as a theoretically grounded but simplistically presented metric to help cities and transportation planners understand holistic impacts of novel and emerging transportation strategies and technologies on the quality of mobility in their jurisdictions. A high MEP score equates to more productive and energy efficient mobility, or more simply, a greater access to opportunities in the context of cost, time, and energy of modes that provide mobility in a location. MEP is used as an evaluation metric for this study as it is desirable to exemplify potential synergistic travel time and energy benefits that this study explores.

Many existing studies use a combination of energy management strategies (EMS) with Intelligent Traffic Systems (ITS). Most of these studies used eco-driving or POEMS with real world traffic data [35-39]. Only a few studies investigated the effect due to synergic application of EMS and optimized Traffic Management Systems (TMS) on fuel economy and traffic efficiency [40, 41]. There is a significant research gap in addressing the effect of application of POEMS and TMS methods simultaneously on fuel economy and mobility. To address this research gap, this paper investigates the effect of POEMS and traffic signal timing optimization on each other's performance. The main contributions include:

- Simultaneous implementation of POEMS and adaptive traffic signal strategy: A validated SUMO model is used along with traffic signal and vehicle optimal controls acting individually and simultaneously.

- Case studies development: Four case studies are developed to evaluate the effect of aforementioned energy and traffic optimization on each other's performance at the corridor in Fort Collins, CO.
- Performance assessment using the MEP metric: MEP metric which documents the combined benefits of improved energy efficiency from POEMS with reduced travel time and improved energy efficiency from optimal traffic signal timing is utilized as an assessment metric.

Methodology

In this section, the experimental method of drive cycle development and real-world data collection is explained. Then evaluated FE and TMS optimization methodologies as well as MEP metric/data overview are discussed. At the end an overview of all studied and developed case studies are presented.

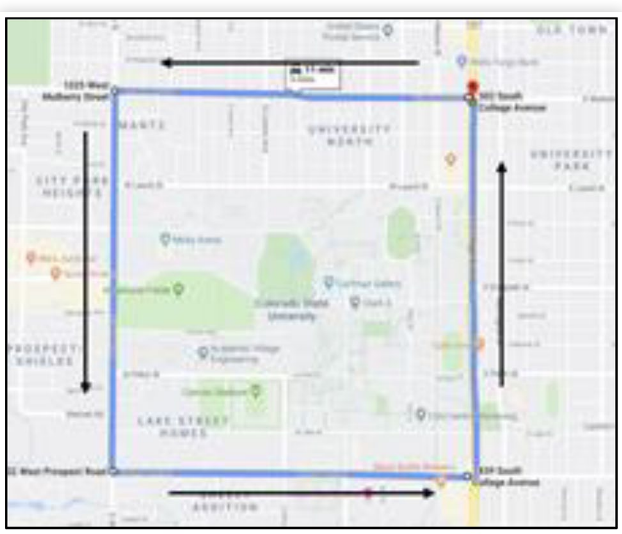
Drive Cycle Development

Over the course of two days, one driver gathered a total of 13 drive cycles. The chosen driving cycle was a 4-mile drive cycle through urban arterial highways in downtown Fort Collins, Colorado. Data gathering followed driving from the College Mulberry intersection to Shield Mulberry intersection to Shield Prospect intersection to College Prospect intersection and back to origin point which is shown in Figure 1.

This drive cycle was selected with the intention that it would be generally representative of urban arterial driving. In order to accomplish this, the drive cycle was selected and tested in order to verify that it was sufficiently similar to the Environmental Protection Agency (EPA) Urban Dynamometer Driving Schedule (UDDS) drive cycle. Figure 2 shows velocity vs. time trace of one of the 13 collected laps of the data drive cycle.

The similarity assessment of characteristics of the data drive cycle and UDDS EPA dynamometer drive cycle was published in a previous study [19].

FIGURE 1 Driving map for selected drive cycle.



FE Optimization

Predictive Optimal Energy Management Strategies (POEMS) for HEVs employs forecasts of future vehicle velocity to determine an ideal powertrain control approach, resulting in improved energy economy. A POEMS, as seen in Figure 3, is made up of three primary subsystems.

1. The perception system, which anticipates vehicle motion based on historical and present vehicle motion, powertrain conditions, driver inputs, ADAS, and V2X (Vehicle to Everything) data.
2. The planning subsystem, which calculates optimal controls based on anticipated vehicle velocity.
3. The vehicle plant, which may be either the actual car or a high-fidelity simulation model of the vehicle.

The outputs of the system are the fuel consumption and change in State of Charge (SOC) of the HEV battery.

Perception Subsystem In order for POEMS to be implementable in real world conditions, the future vehicle velocity must be derived from actual predictions based on available data rather than from prior knowledge of a vehicle velocity trace. Data used in this prediction must also be data which is generally available to connected vehicles. A practical taxonomy of this data is given in Table 1.

FIGURE 2 Velocity vs. time trace of one drive cycle.

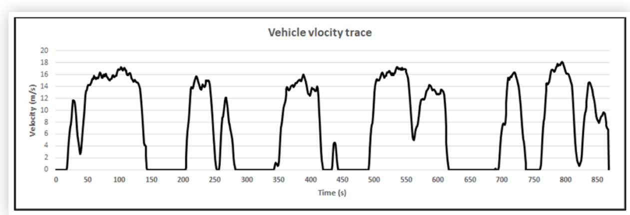


FIGURE 3 POEMS logic system [19].

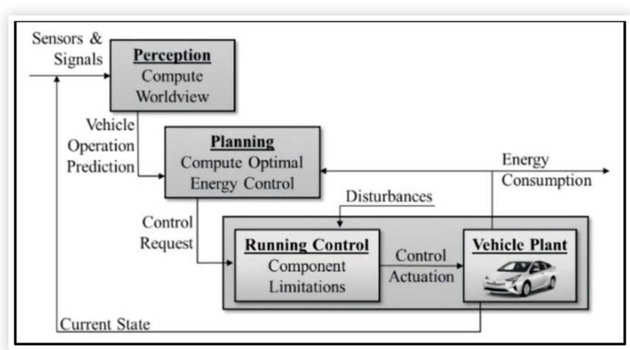


TABLE 1 Data sources and associated signals from [19].

Data Source	Signal	Description
VEH	General Vehicle Signals	Signals such as speed, acceleration, throttle position, and steered angle which can be found via CAN on any vehicle
VEH	Historical Speeds (HS)	Historical speed data for the vehicle at the current location
ADAS	Lead Vehicle Track (LV)	Relative location of confirmed lead vehicle from ADAS system
V2I	Signal Phase and Timing (SPaT)	Signal phase and timing of next traffic signal
V2I	Segment Speed (SS)	Traffic speed through current road segment

The use of various ML and ANN techniques in the creation of future velocity predictions were considered and a deep Long Short-Term Memory (LSTM) ANN was found to be the most effective. The reader is directed to prior publications for more discussion and information [4, 19, 42].

Planning Subsystem The planning system for HEV POEMS can be stated as a classical optimal control problem with the battery SOC and powertrain gear as the states, the torque split and gear shift as controls, and the vehicle velocity as an exogenous input. The objective is to minimize fuel consumption while observing battery SOC constraints.

Solutions to the HEV fuel consumption minimization problem follow two forms. The first is a nominally real time control scheme based on Pontryagin's Minimum Principle (PMP) such as ECMS and a-ECMS [43, 44] and derivative methods. Although nominally real time control methods, these still require future knowledge to compute an equivalence factor which is analogous to a prediction [45]. The second form is DP based methods which compute a globally optimal solution based on a future velocity prediction. DP methods explicitly require high-fidelity predictions to function properly but the exact relationship between prediction quality and DP effectiveness is not known [16].

In order for DP POEMS to be implemented in real time the method must be adjusted to use a limited horizon prediction. The limited horizon prediction is used to generate the optimal controls for the given time-step and the process is repeated at each time step. This method is referred to as Model Predictive Control (MPC). The reader is directed to the prior publication [16] for more discussion and information.

Plant Subsystem In order to maximize the realism of the FE results of the study, the plant subsystem used was a validated Autonomie model of a 2010 Toyota Prius. This model is based on the Autonomie power-split HEV model with the vehicle parameters shown in Table 2 derived from publicly available information about the 2010 Toyota Prius. In lieu of a manufacturer provided model, this Autonomie implementation of a Prius model is as accurate as can be attained.

With these values the model was run for the UDDS, US06, and HWFET EPA dynamometer drive-cycles and the results were compared against those found in Argonne National Lab's Downloadable Dynamometer Database (ANL D^3) [46]. The results of this comparison are shown in Table 3.

TABLE 2 HEV vehicle parameters [19].

Parameter	Value
Overall Vehicle Mass	1530.87 kg
Frontal Area	2.6005 m^2
Coefficient of Drag	0.259
Coefficient of Rolling Resistance	0.008
Wheel Radius	0.317 m
Final Drive Ratio	3.267
Sun Gear Number of Teeth	30
Ring Gear Number of Teeth	78
Battery Open-Circuit Voltage	219.7 V
Battery Internal Resistance	0.373 Ω
Battery Charge Capacity	6.5 Ah

TABLE 3 EPA dynamometer drive cycle FE (km/L) comparison results from Toyota Prius model and Argonne National Lab Downloadable Dynamometer Database [19].

Drive-Cycle	Data	Model	Percentage Difference
UDDS	32.14	31.79	1.09%
US06	29.72	30.30	1.95%
HWFET	19.26	18.98	1.45%

Considering all the above listed discrepancies to be within the acceptable range, the Autonomie Toyota Prius model was used for FE evaluation for this study.

Traffic Optimization

Real-life drive cycles and simulated drive cycles are compared to decide which car following models in SUMO (Simulation of Urban MObility) are most realistic. Parameters for SUMO vehicle configuration inputs are calculated based on real drive cycles used for EMS. The parameters include acceleration rate, maximum speed, deceleration rate, and emergency deceleration rate.

Dynamic Phase Selection and Queue Length Dissipation Sequence Algorithm

SUMO traffic network according to real-life drive cycles is built to demonstrate TMS optimization results and extract drive cycles for EMS optimization. TMS optimization is Dynamic Phase Selection combined with Queue Length Dissipation algorithm (DPS+QLD), which dynamically changes phase sequences and signal timing based on instant traffic volume change.

Dynamic Phase Selection (DPS) Algorithm: Phase Sequence Selection

After a traffic congestion has occurred, typically very few or no vehicles from the approach with minor roads use the green light. Therefore, such a period can be allocated to other phases to improve the mobility of the remaining approaches to avoid long queues. DPS can adaptively choose the best phase sequence of a cycle to make the traffic more efficient with the help from monitoring detectors. Starting at the major road movement, the next phase is chosen dynamically based on all candidate phase options with the following algorithm [47]:

1. Compute the priority for each phase given in the list of indices (the sequence of potential phases that will be used for the next phase when the current one is over) for next possible movements as 'next' attribute. Priority is made according to the number of active detectors for that phase. A detector is deemed "active" when either of the following conditions is met:

    a. The time gap between consecutive vehicles is shorter than the threshold.

    b. Vehicle existence is detected after the signal has turned to red from the last cycle.

2. The current phase is available to continue implicitly if its maximum duration (MaxDur) is not reached. The current phase detector gets a bonus priority.
3. The phase with the highest priority is used for the next cycle over other possible movements.
4. If no traffic is detected, the phases will follow the default cycle defined by the first value in the 'next' attribute.
5. If a particular phase needs to remain active for a no-traffic scenario, it must have a high maximum duration value and its index number is on the 'next' list.
6. If the time that an active detector was not served exceeds the preset time threshold, such a detector will receive bonus priority of the time that was not served. This could prevent those phases serving more traffic from being consistently served.

Based on the algorithm introduced above, DPS can choose the next phase according to the real-time traffic situation. In such a case, a certain amount of time could be saved for better movement of the intersection for other phases.

Queue Length Dissipation (QLD) Algorithm: Optimal Green Light Calculations

After phase sequences are selected, queued-up vehicles on the approach need longer green light time for congestion mitigation. However, the required green time should be calculated based on the queue lengths of not only the current approach, but also other approaches of the intersection at the same time to avoid causing additional congestion in other directions. Therefore, a maximum green time g_{max} should be considered to balance the green time allocations among different approaches. Based on the analytical method by Akçelik [48, 49] , the average green time and cycle length of an actuated controller adopt a fixed unit extension setting by assuming the arrival headway follows the bunched exponential distribution [50]. Existing vehicles remaining in front of the green light are defined as bunched vehicles while new arriving vehicles are defined as free vehicles. Different proportions of bunched and free vehicles define minimum and maximum green time, g_{min} and g_{max} respectively. The green extension time e_g is set based on the queue length at the red light ending time point, and the phase change does not happen during the saturated portion of the green period.

The green time g can be estimated by the following equations introduced by Akçelik [49] :

$$g = g_s + e_g \tag{1}$$

where g is the green time and g_s is the saturated portion of the green period, and e_g is the extension time if the phase change happens after the queue clearance period.

The green time boundary is set as:

$$g_{\min} < g < g_{\max} \tag{2}$$

The green light distribution for the approach with the incident follows the rules considering the queue lengths of other approaches [49]:

$$g = \begin{cases} g_s + e_g, for\, g_s < g_{sj} \\ g_s, for\, g_s > g_{sj} \end{cases} \tag{3}$$

where

g_{sj} = the saturation portion of the green period of other directions and j = 1,2,3.

Traffic signal optimization will be conducted in two phases. During the first phase immediately following the incident, dynamic phase selection (DPS) is used for skipping the unused phase of the blocked approach due to incidents to save the time loss of the intersection operation. The second phase is when the incident is cleared, and the queue length information is collected to calculate the optimal signal timing to dissipate the queue as soon as possible. When g_{max} is reached, the controller will move to the next phase to avoid redundant green time causing long queue lengths on other approaches. After the first cycle, queue length information at the red end time point is collected again for the following signal timing calculations. The traffic signal control optimization covers both crash and recovery stages. DPS is used to skip unnecessary phases during crash stage, and the queue length dissipation algorithm is used to dissipate the queue length at crash lanes as soon as possible. The whole process for this optimization is called DPS+QLD. Assessment metrics for traffic optimization is segment average speed/travel time and is provided as an input to calculate the MEP metric.

MEP Metric & Data Overview

To evaluate the impacts of these case studies on productive, energy-efficient mobility, the MEP metric is calculated for each case using local land use data, travel data, and vehicle characteristics. The MEP metric quantifies access to six types of opportunities (jobs, education, recreation, shopping, healthcare, and meals). This can be done for any given location by computing travel time isochrones, proportioning opportunities access by engagement frequency, and weighting the resulting opportunity measure by time, cost, and energy of any mode that can be used to access the opportunities. This calculation happens in three steps for each location the MEP metric is being quantified at:

1. Quantify the cumulative number of opportunities that a travel mode (e.g., car) can reach within a certain travel time threshold.
2. Normalize all reachable opportunities by a) their relative magnitude of occurrence (e.g., in a city, there typically are a lower number of healthcare facilities compared to retail stores); and b) their engagement frequencies (e.g., healthcare opportunities are engaged less frequently compared to grocery or shopping opportunities). Engagement frequencies are derived from the National Household Travel Survey in 2017 (NHTS) [51].
3. Weight the cumulative opportunities measure using time, energy, and cost decay functions such that more weight is assigned to modes that provide faster, affordable, and energy-efficient access to opportunities.

The equation to compute MEP can be mathematically described as follows:

$$MEP_i = \sum_k \sum_t \left(o_{ikt} - o_{ik(t-10)} \right) \cdot e^{M_{ikt}} \tag{4}$$

where

o_{ikt} = the opportunity measure, which represents the number of opportunities that can be reached by mode k in time t from location i; and M_{ikt} is further defined as:

$$M_{ikt} = \alpha e_k + \beta t + \sigma c_k \tag{5}$$

where:

M_{ikt} = Composite decay function for time, energy, and cost

e_k = the energy intensity in kWh per passenger-mile of mode k

t = is the travel time in minutes

c_k = the cost in dollars per passenger-mile of using mode k

α, β, and σ= the weighting parameters

The weighting parameters for α (energy), β (time), and σ (cost) are −0.5, −0.08, and −0.5, respectively. For more details on the MEP methodology see [33, 34].

MEP can be applied to multiple modes (e.g., walking, transit, biking, driving), but for this analysis we focus on impacts to light-duty vehicles driving on the specified route in Fort Collins, CO. The drive mode MEP is calculated using a routable road network in Fort Collins with average vehicle speeds for all road links in the region, and activities by type are evaluated using parcel level third-party land use data. We translate fuel economy improvements and travel speed improvements from simulations outlined in above sections to the baseline real-world observed speeds by link and average driving fuel economies to evaluate optimization scenarios on MEP scores in the case study area.

Case Studies

In order to evaluate the individual and combined effects of POEMS and TMS on system level MEP, a series of four scenarios was evaluated in the SUMO model of Fort Collins, Colorado. The scenarios were defined as follows:

Case Study 1: EMS (baseline) + TMS (baseline)

Case Study 2: EMS + Optimized TMS

Case Study 3: TMS + Optimized EMS (POEMS)

Case Study 4: Optimized EMS (POEMS) + Optimized TMS

In each case, vehicle trajectories were generated using SUMO and then EMS was applied post-hoc to those trajectories. Because EMS does not affect vehicle trajectories and TMS does not use vehicle fuel economy as an input, EMS does not need to be applied in-loop with TMS.

Case Study 1:

In the first case study the baseline EMS and baseline TMS using validated Autonomie and SUMO, models are developed, and corresponding baseline fuel economy and travel time are calculated.

To calculate the baseline travel time from SUMO, abstracted drive cycles including key parameters are fed along with traffic volume, traffic network, vehicle model, and route information. The key parameters from drive cycle abstraction include acceleration rate, maximum speed, deceleration rate, and emergency deceleration rate.

After calculating these parameters from real-life data, the acceleration rate is 1.9 m/s^2, deceleration rate is 2 m/s^2, and emergency deceleration rate is 6 m/s^2. By comparing different car following models in SUMO, EIDM (Extended Intelligent Driver Model) is selected to represent the human driver behavior because the travel time and lane change behavior are most close to real-life data. Table 4 shows the results comparison from SUMO using EIDM and real-life data driving the same route of the network.

Case Study 2:

The second case study considers the effect of optimized TMS (traffic signal time optimization) along with baseline EMS on travel time and fuel economy values respectively.

Case Study 3:

The third case study considers the effect of baseline TMS along with optimized EMS (POEMS) on travel time and fuel economy values respectively.

Case Study 4:

The fourth and last case study considers the effect of optimized TMS (traffic signal time optimization) along with optimized EMS (POEMS) on travel time and fuel economy values respectively.

TABLE 4 Comparison results from SUMO model (EIDM) and real life data.

Parameters	Real-Life Data	EIDM
Travel time (s)	770	737
Travel distance(m)	6480	6506

Results and Discussion

Figure 4 shows a comparison of the optimized results based on running vehicles at each simulation time point (a), average travel time vs simulation time step (b), and average speed vs time step (c) with validated simulation results (case study 1 and 2).

Case Study MEP Impacts

For the four case studies outlined, we evaluate MEP impacts to the area immediately surrounding the driving route (shown in Figure 1), which is defined as a 250 m^2 buffer bounding box around the driving route. Table 5 presents the MEP impacts for all four cases (case 1 being the baseline), and Figure 5 displays the spatial impact of each case to MEP at a 250 m^2 grid resolution. Improvements are observed to be the strongest along the southern part of the case study area along Prospect Rd in all three optimal scenarios. While traffic signal corridor optimization in the optimal TMS only case improves travel speeds and fuel economies along the route (as opposed to only fuel economies and no effective impact on overall speed in optimal EMS only), the optimal TMS only case shows the smallest improvement. While the TMS optimization generally optimizes travel speeds on most of the links (up to 8 m/s improvement over baseline and a link-length weighted average of 20%), travel speeds on some links are sacrificed for greater corridor improvements (e.g., some link segments on College Ave have slightly decreased speeds around -1 m/s from baseline). This could be construed as a more realistic case (where speeds on some links are improved at the cost of reduced speeds on others) as opposed to the optimal EMS case, where the network efficiency (i.e., travel speeds on the links) is assumed to be practically immune to the efficiencies brought about by improved fuel economy. Further investigation into the tradeoffs in EMS only and TMS only scenarios is warranted.

The cumulative improvement from combined EMS and TMS optimization also results in MEP improvements that surpass the arithmetic summation of MEP impacts EMS only

FIGURE 4 SUMO Network.

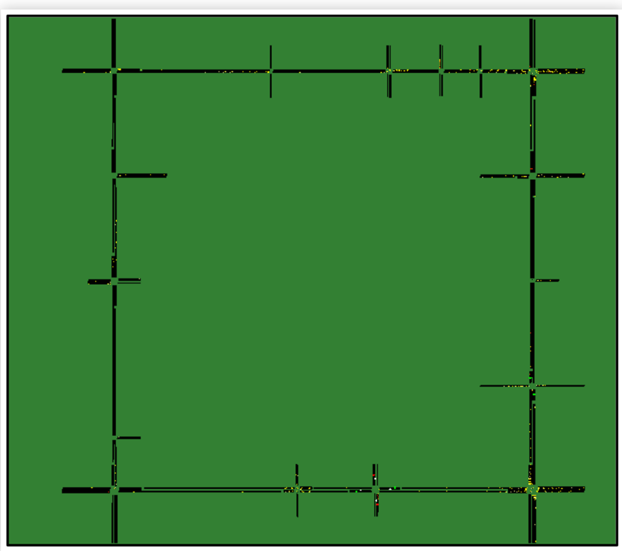


FIGURE 5 comparison of running time (a), Travel time (b) and Average speed (c) vs. time for case studies with baseline TMS (case study 1 and 3) and optimized TMS (case study 2 and 4)

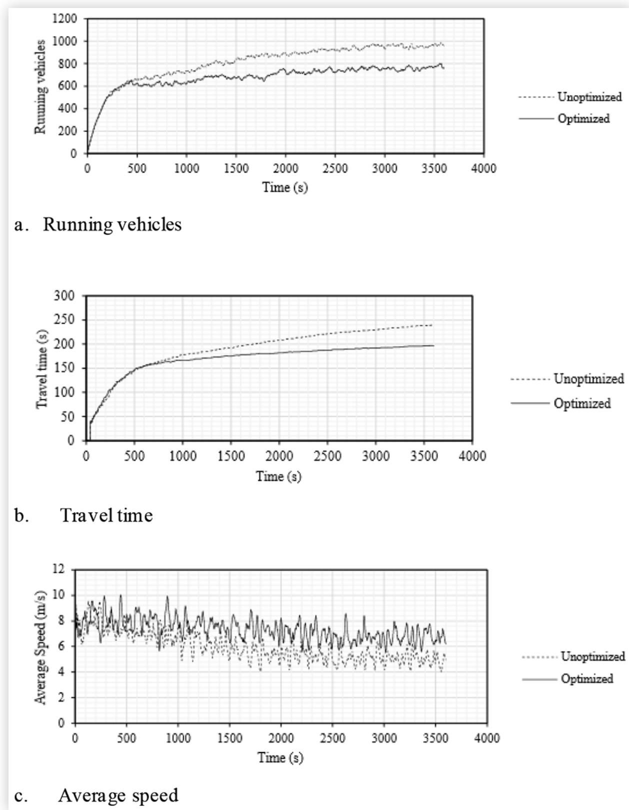
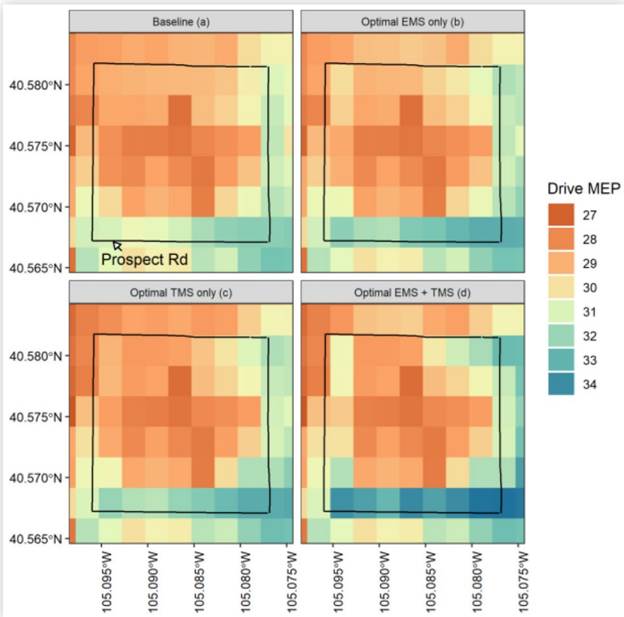


TABLE 5 MEP impacts for four case studies evaluated. These impacts consider MEP scores only in a 250 m^2 buffer around the route in Fort Collins, Colorado. For these results, the road-miles impacted was 8.2% of all road-miles in the study area (i.e., most links in the area are not modified with improvements). TT = Travel Time.

Case Study		Mean FE and TT Improvements	Drive MEP	Relative MEP Improvement
1	Baseline	-	29.36	-
2	Optimal TMS only	16.1% FE; 20% TT	29.44	0.28%
3	Optimal EMS only	17.7% FE; 0% TT	29.60	0.82%
4	Optimal EMS+TMS	43.2% FE; 20% TT	29.82	1.57%

FIGURE 6 MEP scores at 250 m^2 resolution for the four scenarios (a-d) simulated. The driving route which had modified speed and fuel economies is labeled in (a) and shown as a black line overlay.



and TMS only optimization. The increase in cumulative gains is derived primarily from the increase in FE for the optimal EMS+TMS case. This shows that the combination of optimal EMS and TMS in concert is best for increasing the quality of driving accessibility in terms of MEP. It is often the case that EMS and TMS optimizations are conducted and implemented in isolation as the stakeholders interested in these improvements are fairly disjoint. While the traffic operations community is primarily responsible for finding and implementing TMS improvements, EMS improvements come from vehicle manufacturers. The result here corroborates that idiom "The whole is greater than the sum of the parts," and that it would be beneficial for both vehicle and traffic system communities to come together for delivering the greatest (MEP) benefits to the travelers.

It is important to note here that the case studies evaluated show realistic impacts that are achievable for only improvements on a small corridor (roughly 2 km^2 area with only 8.2% of road-miles simulating optimization). We tested a scenario that translates the average improvements by road class across the whole city of Fort Collins, CO, and found that an optimal TMS and EMS case that applies to 7.2% of road-miles across the city improved the city-wide MEP score by 18.5%. This shows that EMS and TMS optimization when applied at scale may result in significant improvement of the mobility and energy efficiency of a city's transportation system. Full network optimizations need to be tested to corroborate this claim.

Summary and Conclusions

In a connected world, vehicles and infrastructure can and must be developed in a synergistic manner in order to enable the greatest efficiency for a given transportation system as a whole. Using previously developed optimal EMS and optimal TMS methods individually and in tandem, this study demonstrates that substantial additional fleet level efficiency benefits may be attained by the application of both simultaneously over the combined effects of each individually. FE improvements of 16.1% and 17.7% over baseline were obtained respectively from the application of optimal TMS and EMS individually where a 43.2% improvement over baseline was obtained from their simultaneous application. These FE improvements, combined with travel time improvements from optimal TMS, resulted in MEP improvements of 0.28% and 0.82% for optimal TMS and optimal EMS respectively and 1.57% for the application of both simultaneously. In both FE and MEP terms the improvements from the application of both optimal EMS and optimal TMS were greater than the sum of the individual improvements. The results of this study illustrate the fundamental interconnectedness of vehicle level and infrastructure level energy optimization and underscore the importance of the benefits which can be attained through connectivity. Overall, by finding evidence of a positive synergistic relationship between vehicle and transportation system level optimal controls this study lays the groundwork for a new direction of research in collaborative development between transportation stakeholders to optimize system level efficiency.

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Definitions/Abbreviations

ADAS - Advanced Driver Assistance Systems

ANL D3 - Argonne National Lab's Downloadable Dynamometer Database

ANN - Artificial Neural Network

CAV - Connected and Automated Vehicle

DP - Dynamic Programming

DPS - Dynamic Phase Selection

ECMS - Equivalent Consumption Minimization Strategy

EIDM - Extended Intelligent Driver Model

EMS - Energy management System

EPA - Environmental Protection Agency

FE - Fuel Economy

GHG - Greenhouse Gas

HEV - Hybrid Electric Vehicle

ICE - Internal Combustion Engine

ITS - Intelligent Traffic System

LSTM - Long Short-Term Memory

MaxDur - Maximum Duration
MEP - Mobility Energy Productivity
ML - Machine Learning
MPC - Model Predictive Control
NHTS - National Household Travel Survey
NREL - National Renewable Energy Laboratory
PHEV - Plug-in Hybrid Electric vehicle
POEMS - Predictive Optimal Energy Management Strategy
QLD - Queue Length Dissipation
SOC - State of Charge
SUMO - Simulation of Urban Mobility
TMS - Traffic Management System
TT - Travel Time
UDDS - Urban Dynamometer Driving Schedule
V2I - Vehicle to Infrastructure
V2V - Vehicle to Vehicle
V2X - Vehicle to Everything

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