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ENERGY CONSUMPTION REDUCTION STRATEGIES FOR PLUG-IN HYBRID ELECTRIC VEHICLES WITH CONNECTED VEHICLE TECHNOLOGY IN AN URBAN ENVIRONMENT

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ABSTRACT

Automobile manufacturers have introduced plug-in hybrid electric vehicles (PHEVs) to reduce fossil fuel consumption. This paper details three optimization strategies that can be utilized to further minimize energy consumption of PHEVs through an information exchange between PHEVs and infrastructure agents supported by the connected vehicle technology (CVT). While an earlier research by the authors focused on a freeway scenario, this study developed strategies for an urban scenario in which frequent 'stop-and-go' conditions exist. Three strategies were considered in this study based on different types of information availability using CVT; only signal timing information was available in Strategy One, only headway information was available in Strategy Two, and both signal timing and headway information were available in Strategy Three. The performance of PHEVs that received no real-time information was used as the base case for Strategies One, Two or Three to evaluate each strategy. The optimization strategies resulted in energy consumption savings ranging from 60% to 76%. An analysis with various levels of penetration of CVT-supported PHEVs in the traffic was conducted to demonstrate the impact of these optimization strategies with their increased market share. For a case study network, the authors found a linear trend between energy savings and penetration rate of CVT supported PHEVs. The Strategy Three in which signal timing and headway data were provided to CVT supported PHEVs, resulted in about 31% to 35% energy savings with 30% penetration of CVT supported PHEVs at the peak hour volume.

Keywords: Energy consumption reduction, Signal timing, Headway, plug-in hybrid electric vehicle

1.0 INTRODUCTION

The instability of the crude oil market over the last few years has resulted in a substantial fluctuation in gas prices *(1)*. Such instability was one of the main reasons to create alternate energy sources for automobiles which led to the development of alternative fuel vehicles (AFVs) to increase US energy independence. Further, AFVs such as plug-in hybrid electric vehicles (PHEVs) utilize both power sources, conventional gasoline and electricity, which enables an efficient transition of the transportation network from fossil fuel to renewable energy resources. Minimizing the energy use in PHEVs has been the subject of intensive research since their conception. The combination of electric drivetrain and conventional gasoline drivetrain in PHEVs improves fuel economy and reduces harmful emissions. PHEVs emit approximately 32% fewer greenhouse gases than conventional vehicles do over their lifetime *(2)*. Even though their current penetration on the road today is small, PHEVs can significantly reduce net CO_2 emissions *(3)*.

Another new facet of Intelligent Transportation Systems (ITS) technology that has emerged in recent years is the concept of Connected Vehicle Technology (CVT). CVT can provide real-time traffic data by supporting real-time vehicle to vehicle and vehicle to infrastructure (e.g., traffic signals, traffic sensors) communication, which can be used for different applications such as en route decision support *(4, 5)*. The PHEVs can utilize real-time traffic data to identify when to use battery power and when to use gasoline, thus reducing total energy consumption in the vehicles.

In this paper, the authors evaluated the impacts of CVT supported PHEVs on a signalized roadway network. The authors considered the following three different data transmission scenarios.

1. Traffic signal timing information: In this scenario, the authors assumed that en route signal timing information is available to all CVT supported PHEVs in the network. The signal state information for every signal in a roadway network was obtained as an output from a traffic micro-simulation model and driving profile for each PHEV was optimized for fuel savings using the available information.
2. Headway information: In the connected vehicle environment, any CVT supported vehicle can get en route headway information from other vehicles as well as roadway sensors. In this scenario, the authors assumed that the headway information is available to vehicles via other vehicles and/or infrastructure sensors. The headway information was obtained from a traffic micro-simulation model.
3. Traffic signal timing and headway information: This scenario was a combination of scenario one and two and the authors assumed that both en route signal timing and en route headway information were available to each CVT supported PHEV in the network to optimize its driving profile.

It should be noted that the traffic signal timing information implies that each CVT supported PHEV has access to the signal state, (i.e. Red, Green or Amber) for every signal in the roadway network at every second. Similarly, the headway information implies that each PHEV knows headway between the leading vehicle and itself at every second of the trip. The detailed strategies for these three different scenarios are explained in the methods section.

2.0 RELATED WORK

Urban traffic flow cannot be evaluated without evaluating the flow at signalized intersections, the purpose of which is to separate conflicting movements to improve safety *(6)*. By separating the movements in time, the traffic signals add delay to the respective movements, which in turn results in to congestion for urban scenarios. The congestion leads to increased travel time and fuel consumption *(7, 8)*. The recent awareness about the global environmental concerns and the instability of gas prices *(1)* has helped create the market for different Alternative Fueled Vehicles (AFVs) in the United States. Though PHEVs and EVs reduce emissions compared to fossil fuel vehicles *(2, 9)*, the drivers of the AFVs still have the same concerns of increased fuel and/or energy consumption. Thus, this research focuses on reducing energy consumption by utilizing traffic signal data and headway data for PHEVs. Below the authors detail the related work on saving energy consumption or fuel consumption at signalized intersections for conventional vehicles and PHEVs /AFVs.

2.1 Signal timing techniques and conventional vehicles

Signal timing methods have evolved from flexible-progressive pre-timed systems to that of centralized and distributed adaptive traffic control *(10)*. Researchers have since applied different methods to optimize the signal timing, most particularly the local actuation Time of Day (TOD) method *(10)* and various offline optimization methods *(11)*. Smith et al. used archived traffic data and statistical cluster analysis to identify TOD intervals *(12)*. Here, they automated the process of selecting the TOD interval break points, a method that was enhanced by Park et al. utilizing a Genetic Algorithm (GA) based on the clustering approach *(13)*. They used the micro simulation program SIMTRAFFIC and evaluated the results with actual timing data. Park et al. also enhanced the GA based method by implementing two-stage optimization, which resulted in obtaining the break points in a smaller number of iterations *(14)*. Similar research has involved the use of mathematical models, and real-time signal coordination models *(15)* to develop coordination scenarios by utilizing vehicle delays, fuel consumption and emissions at intersections *(8)*. Though effective in reducing fuel consumptions and emissions at the network level, these models use the platoon of vehicles for optimization, which may or may not include all the vehicles passing through the intersections. In addition, with the change in traffic volumes over time, the optimized signal timing algorithms gets outdated. Further, without CVT, individual vehicles cannot utilize the timing information to optimize the vehicle performance.

2.2 Connected vehicle technology and Alternate Fueled Vehicles

CVT can be utilized to optimize vehicle performance and concurrently reduce energy consumption and emissions. The energy consumption can be reduced either by modifying signal timing for approaching vehicles or by informing the status of the signal to the driver ahead of time. Transit signal priority is one example of modifying the signal state, which is widely used but limited to high occupancy vehicles, commonly buses. The recent research conducted by Li et al. focused on informing drivers of cars about the signal status, finding a potential 8% reduction in CO_2 emissions *(16)*. Rakha and Kamalanathsharma developed an objective function which provides the fuel-optimal speed profile for a vehicle to safely cross an intersection *(17)*. Schuricht et al. developed a driver assistant system which utilizes traffic condition data and traffic signal information to reduce fuel consumption *(18)*. Zhang and Vahidi predicted the speed profile based on the speed limits of the route and optimized the energy consumption globally for the trip as well as locally based on power demand, SOC, and other global optimization parameters *(19)*. Asadi and Vahidi developed a predictive cruise control strategy for a conventional vehicle, which uses the adaptive cruise control function *(20)*. These studies are focused on fossil fueled vehicles and none considered the unique characteristics of PHEVs.

Most similar to the work herein, He et al. conducted a study on driving cycle optimization for PHEVs, in which the ITS based predictive driving cycles were optimized before sending them to PHEVs for energy optimization. They concluded that it is possible to improve the energy efficiency of PHEVs by utilizing ITS communication capabilities (i.e. Connected Vehicle Technology) for the energy management system and the cycle optimization algorithm *(21)*. However, because the roadway network used in the study was a freeway network, the signal information was not considered. This research extends the driving cycle optimization research of He et al.*(21)* and others, yet focusing on the urban scenario. In contrast to freeway networks, this study includes stop-and-go traffic and the interaction between vehicles and signals, making the driving cycle optimization more challenging.

3.0 METHOD

The research method was divided into two phases. The first phase focused on developing strategies to optimize PHEV performance in an urban environment. A traffic simulation model of a roadway network with signalized intersections was developed in the second phase to apply these strategies.

3.1 Phase 1: Optimization Strategies

It is well known that frequent stop-and-go behavior in an urban traffic is one of the leading causes of high energy consumption for any vehicle irrespective of type and/or fuel source *(22)*. The basic idea of the optimization in this study is to reduce the frequency of speed changes. Specifically, this study focused on speed changes because of (i) frequent stops at signals and (ii) frequent acceleration and deceleration due to headway changes between the preceding vehicle and the subject vehicle. In addition, it was also assumed that the subject vehicle would receive signal timing and headway information for the segment via other vehicles and nearby infrastructure sensors. Therefore, instead of optimizing for the entire trip, the optimization was conducted in the segments divided by signalized intersections. The details of the three strategies developed based upon availability of information are described in this section.

3.1.1 No Strategy (Base Case): No information available

This case works as a base line for this study since no information is available for any vehicles to optimize their travel.

3.1.2 Strategy One: Only signal timing information available

For the first strategy, the authors assumed the availability of signal timing information to a vehicle via the wireless connection between the vehicle and the infrastructure sensors, and the unavailability of headway information. Therefore, the procedure included an optimization stage and a post-processing stage as shown in Figure 1. At the optimization stage, the goal is to avoid stopping when the signal is red; the driving cycle outputted at this stage meets the signal constraints and maintains a constant speed within the segment. The first step of the optimization stage is to obtain a base location profile, i.e. the average speed of the target vehicle or the average speed of the segment in the case of a zero total distance travelled. If the vehicle expects to arrive at a signal during the red interval, a new constant speed is calculated, at which the vehicle arrives on a green interval. After the location profile is optimized with respect to signal information, the strategy goes into the post-processing stage.

Because, in the optimization stage the optimized driving profile ignores headway information, it is necessary to modify the driving profile using existing headway information in the post-processing stage. For the case study, the headway information obtained from simulation output was used as a constraint. The reactions to headway changes were added to the driving cycle from the previous stage cycle so that it meets the headway constraints. Note that it is possible that the modified location profile may result in stopping at signals because the headway information is disregarded during the optimization stage; therefore the location profile may require further modification to reflect the behavior of stopping at the signal. The entire process was repeated for all segments of the route, and then the location profile of entire route was obtained.

3.1.3 Strategy Two: Only headway information available

Unlike strategy one, which represented only vehicle-to-infrastructure communication, this strategy represents both vehicle-to-vehicle and vehicle-to-infrastructure communication. Similar to Strategy One, the process has an optimization stage and a post-processing stage as shown in Figure 1. Only headway information is assumed to be available for the optimization stage, however. The goal of the optimization stage is to avoid unnecessary acceleration/deceleration with respect to headway information; the output from this stage is a location profile with constant speed that meets the headway constraint.

At the optimization stage, a location profile was created with the maximum constant speed that the target vehicle can maintain without passing a preceding vehicle. Since this location profile ignores the state of the en route signal, the signal timing information obtained from simulation output was used as constraint in the post-processing stage. Possible stopping at a red signal was added to the optimized location profile at the post-processing stage. The location profile was then further modified if the vehicle must stop at a signal. The entire process was repeated for all segments of the route to obtain the location profile for the entire route. Note that in this case, there is no need to re-check headway information because the signal is always at the end of each segment; thus stopping at a signal does not affect the location profile within the current segment and headway information is current when the vehicle enters the next segment.

3.1.4 Strategy Three: Both signal timing and headway information available

Since this strategy utilizes both the signal timing and headway information, it involves only an optimization stage, as shown in Figure 1, which means that both signal timing and headway information are available for the optimization. A combined constraint in terms of location with respect to time was obtained by combining the signal timing and headway. A location profile was then created with the maximum constant speed that the target vehicle can maintain without violating the constraint. The process was again repeated for each segment to obtain the location profile for entire route.

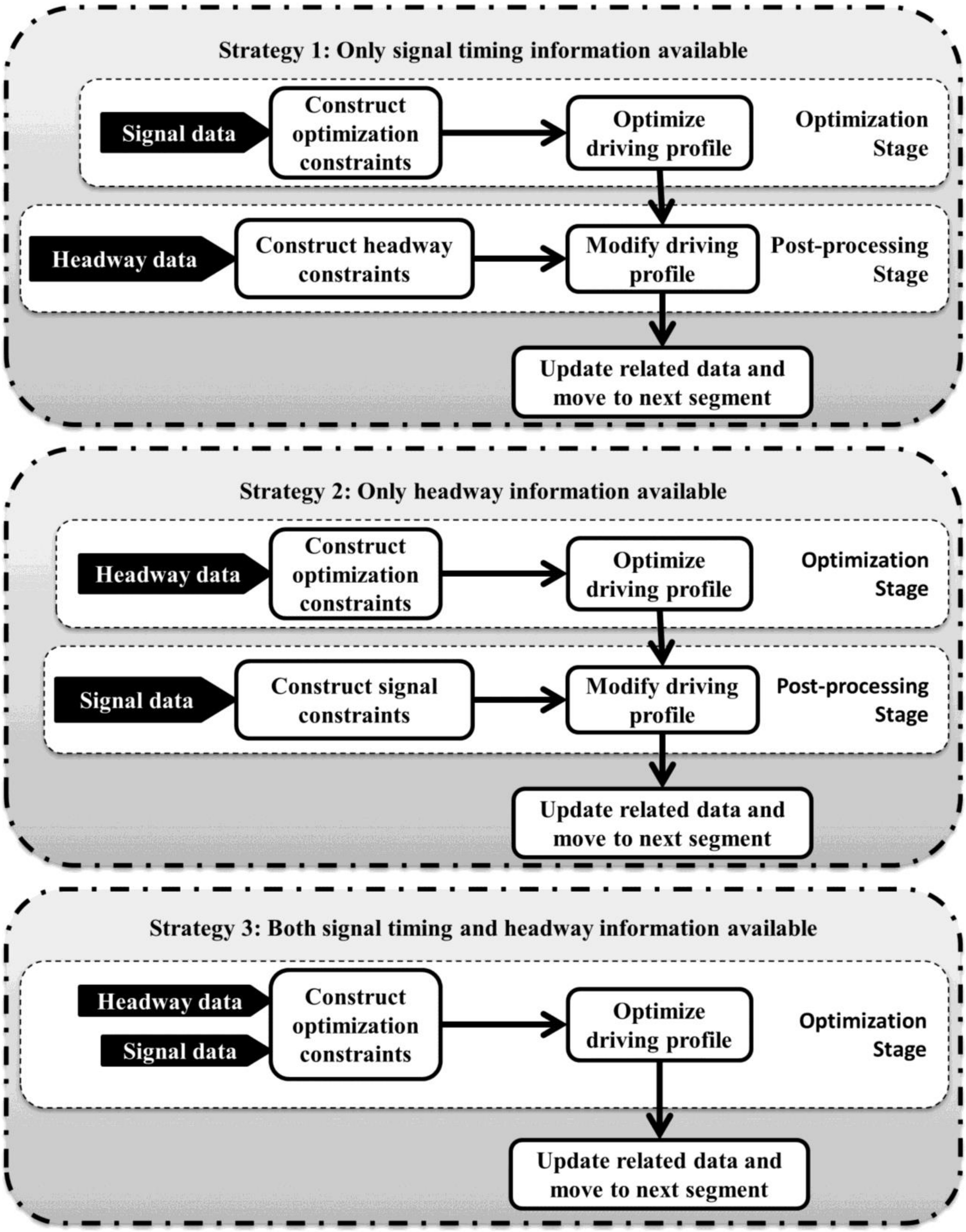

FIGURE 1 Energy consumption reduction strategies

3.2 Phase 2: Evaluation of strategies

3.2.1 Traffic Simulation model development

The second phase entailed developing the calibrated and validated VISSIM model to generate different cases for evaluation. The authors considered a network of Hwy 93 in Clemson, SC, which included a downtown intersection of College Avenue and 93 along with the peripheral intersections of Clemson University. Intersection related data (e.g. volumes, signal timings and travel times) were collected during the peak hours of traffic, which was in the evening. The authors next developed a network in Synchro and optimized signal timings to replicate the timing during the peak hours of traffic. It was assumed that signal patterns did not change during those peak hours and that the intersections will behave as fix-timed signalized intersections. The VISSIM network as shown in FIGURE 2 was then developed by exporting the Synchro network, different components of which (e.g. signal head locations, reduced speed areas) were then checked for accuracy. A visual inspection of the traffic at each intersection was undertaken using multiple simulation runs of the network.

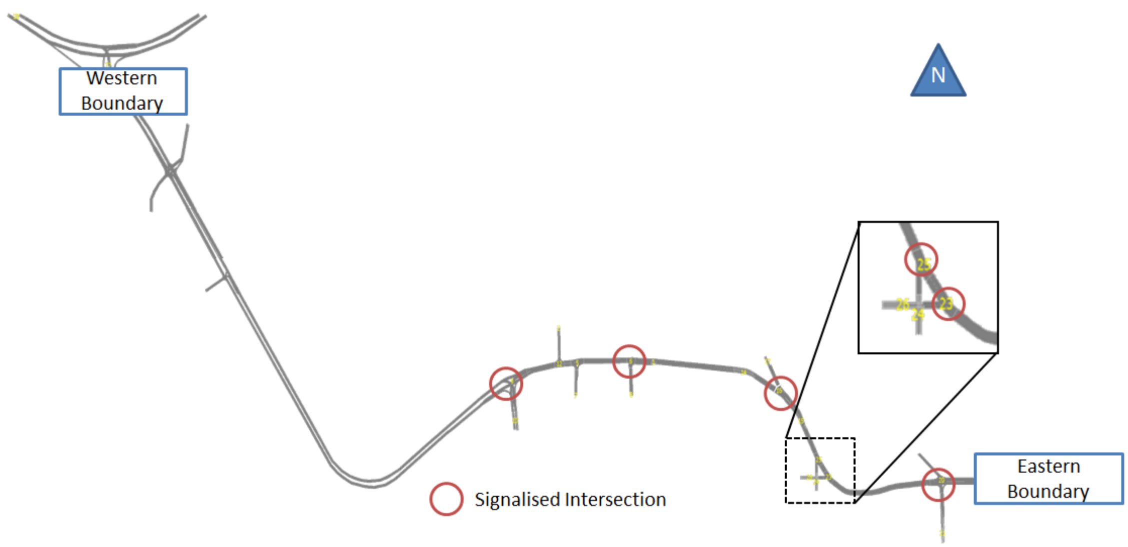

FIGURE 2 Highway 93 Network in VISSIM

In that a calibrated roadway network represents real world scenarios with a certain degree of accuracy, a calibration process is necessary for any traffic simulation network. To achieve the desired level of accuracy, different parameters such as headway and desired speed distributions were adjusted in the simulation. The network was then simulated again and the travel time data of the main route was compared with the field travel time data. This process was repeated until the average travel time for a simulation network was within the 10% range of the observed travel time. The average travel time of a single simulation run need not represent the mean of the population, i.e. the true mean of the simulation travel time, however. Thus, the seed value for the simulation was varied from 26 to 65 and the average travel time was gathered for each simulation run. The mean and standard deviation of this sample was used to calculate the sample size. The authors found that 40 samples were required to find the true mean of the population with a 1.5% error rate. The next step in the process involved determining the best seed value for a simulation which is very close to the mean of the field data. The seed value of 35 was best suitable for this network, which was again simulated with a seed value of 35 and travel time data collected at every 600 seconds. The t-test was then performed for each direction of Highway 93 with the null hypothesis to ensure a zero difference between the mean of the simulation travel time and the observed travel time. The authors found significant evidence (α=0.05) to support the null hypothesis. Thus the calibrated model with a seed value of 35 represented the real-world scenario. This model was then used for further analysis.

3.2.2 PHEV Model

A previously developed MATLAB-Simulink PHEV model *(21)* was utilized to evaluate the energy consumptions of PHEVs, the detailed configuration of which is shown in Table 1. Since driver behavior is not the focus of this research, the PHEV model was assumed to follow the driving cycle closely without considering the driver error. The PHEV model adopts power-split drivetrain, which is the most widely used drivetrain in real-life *(23)*. The power-split device splits power among the internal combustion engine and two motor/generators; the Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) was utilized to optimize such power-split.

TABLE 1: Vehicle Model Specifications*

Total weight of the vehicle	1330 kg
Projected frontal area of the vehicle	2.16 m^2
Aerodynamic drag coefficient	0.26
Rolling friction coefficient	0.007
Transmission efficiency	0.98
Final gear ratio	4.11
Engine power	57kW @5000rpm
Motor/Generator1(MG1) power	30kW
Motor/Generator2(MG2) power	50kW
Battery construction	168 cells of 6.5-Ah cylindrical battery in a series for each pack
Total Battery packs	3
State of Charge (SOC) window size	30% ~ 80%

* This table is adapted from reference *(21)*

3.2.3 Conventional Vehicle Model

A MATLAB-Simulink model was also utilized to evaluate the energy consumption of conventional vehicles in the network. For purposes of comparison, the parameters of conventional vehicle model were kept identical to the PHEV model except that the conventional vehicle model does not have electric drivetrain.

3.2.4 Testing Scenarios

The authors developed three VISSIM models based upon the volume levels: 1) 90 percent of the peak hour; 2) 100 percent of the peak hour, and 3) 110 percent of peak hour. The signal timing data for each intersection in the network, speed profile data for each vehicle, and headway data for each vehicle were collected from each VISSIM model. The collected data was then utilized to estimate energy consumption for PHEVs under different optimization strategies as well as conventional vehicles. As shown in Figure 2, VISSIM network included six signalized intersections on Highway 93.

The authors developed two different experimental scenarios for VISSIM models.

- In the first scenario, vehicles traveling the longest distance from the eastern (EB Highway 93) to the western boundary (WB Highway 93) were considered, which included all intersections of the network. For our base cases, vehicles traveling on WB and EB were replaced with the PHEVs. The average energy consumption for each PHEV was obtained by simulating the PHEV model using the speed profile collected from VISSIM model. We then applied optimization strategies to the same set of vehicles as the base cases.
- For the second scenario, the impact of different levels of penetration was studied. For each VISSIM model, the PHEV percentage was varied from 5 to 30 percent at increments of five percent. The same signal timings were used for all VISSIM models. This scenario included two parts. In the first part, the penetration rates were varied for each OD pair in the network; in the second part, the penetration rates were varied randomly for entire matrix regardless of the origin-destination pair.

4.0 ANALYSIS

Figure 3 shows an output from the cycle optimization strategies for a randomly selected eastbound (EB) vehicle from the simulation with 100 percent of the peak hour volume. The three different strategies are denoted by number. As can be seen in Figure 3, the optimized cycles were less aggressive compared to the original cycle (denoted by '0' in Figure 3) and for Strategies Two and Three PHEVs took longer time to traverse the corridor. Consequently, the cycle in

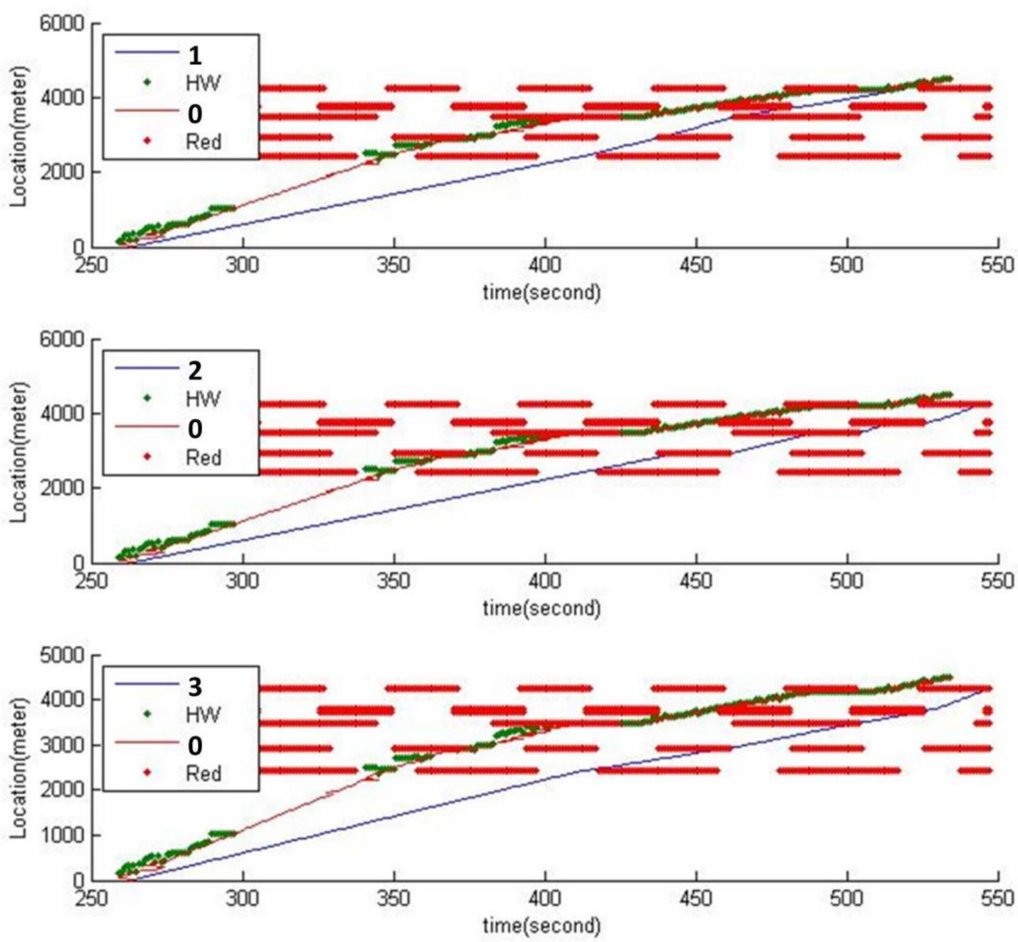

FIGURE 3 Sample Cycle Optimization Output

Strategy One ('1' in Figure 3) was unlikely to be limited by headway. However, the vehicle may still stop at signals in Strategy Two ('2' in Figure 3). For Strategy Three ('3' Figure 3), since both the signal timing and the headway were considered in the optimization, minimum speed adjustment was needed.

Since there were two energy sources in this study, total monetary cost was calculated in order to properly compare the performance between each scenario. The unit prices for gasoline and electricity considered for the study were \$3.394/gallon *(24)* and \$0.01191/Kwh *(25)*. Figure 4 shows a boxplot for each scenario. It should be noted that, the PHEV base case, refers to the case where all vehicles in the network were replaced by PHEVs without CVT support.

Table 2 provides a detailed energy savings with respect to conventional vehicles and the PHEV base case (No Strategy) to more closely ascertain how each strategy improves energy efficiency. Since the results for each scenario were not normally distributed, the energy savings calculations in Table 2 were performed using the medians of resulting data. As expected, Strategy Three was found to exhibit the greatest improvements in efficiency, followed by Strategy One and Strategy Two. Strategy One (optimizing for the signal timing information and reacting to the headway information) performed better than Strategy Two (optimizing for the headway information and reacting to the signal information) because number of stops were minimized in Strategy One and the number of speed changes were minimized in Strategy Two. Therefore, Strategy Three, which minimizes both the number of speed changes and the number of stops, exhibited the best energy-consumption performance.

A comparison of various volume levels (90%, 100% and 110%) given in the Table 2 suggests that the 100% volume model was the most improved of all strategies, followed by the 110% volume model, and the 90% volume model. The reason behind these results may be the vehicle-oriented optimization strategies instead of network oriented strategies. That is to say the energy savings achieved from the strategies are limited by the network conditions. While the strategies focus on reducing the number of unnecessary speed changes, this number is low at both high and low congestion levels. While at the low congestion level, the vehicles are more likely to travel freely and the number of unnecessary speed changes is small; at the high congestion level, the number of speed changes increases and most of them are necessary because the movements of vehicles are limited by the traffic. Therefore, the combined effect of these factors complicates the relationship between the energy improvements from these strategies to the traffic volume of the network.

TABLE 2: Energy Savings in Each Scenario

Volume	**Base**	**No Strategy**	**Strategy One**	**Strategy Two**	**Strategy Three**
90%	Conventional	70.79%	89.82%	88.33%	91.11%
	PHEV Case0	-	65.16%	60.06%	69.57%
100%	Conventional	71.85%	91.70%	91.16%	93.04%
	PHEV Case0	-	70.51%	68.59%	75.27%
110%	Conventional	71.09%	90.78%	88.90%	91.43%
	PHEV Case0	-	68.09%	61.61%	70.35%

Note the energy savings compared to the base case grouped by different numbers of signals in Figure 5, in which the optimizations were conducted within the segment divided by signals to ensure accuracy in prediction. Though possible speed changes between segments reduced the savings as indicated, going through more signals resulted in increased stop-and-go situations for optimization. The second testing scenario included a two-part penetration study in which the penetration rates of CVT-PHEVs (the percentage of CVT-PHEVs in the traffic) were varied from 5 percent to 30 percent with 5 percent increments. In the first part, the penetration rates were equally distributed for each OD pair in the network; the energy savings compared to 100% conventional vehicles are shown in Table 3 Part 1. In the second part, although the total penetration rates are same as the one in the first part, the penetration rates for each OD pair is random; the energy savings are shown in Table 3 Part 2. As can be seen in Tables 3, all three strategies are superior to the baseline, with Strategy Three performing better than Strategies One and Two. The performance of all three strategies remained consistent with different volume levels.

5.0 CONCLUSIONS

The authors evaluated the efficacy of energy consumption reduction strategies for CVT supported PHEVs in an urban scenario, in which CVT provided traffic signal and headway information to PHEVs to minimize their energy consumption. The analysis suggests that PHEVs with CVT yielded between 60 to 80 percent savings in energy consumption compared to PHEVs without the CVT. Of the three CVT-based strategies developed in this study, the strategy that utilized both the signal and headway information exhibited the best performance for energy savings (about 75 percent). Strategy One, utilizing only signal timing information, reduced the energy consumption by about 71 percent. The findings of this study imply that Strategy Two, which utilized only the headway information, could still save about 68% percent of PHEV energy consumption. A penetration study was also conducted in which the penetration rates of CVT supported PHEVs (i.e., the percentage of CVT supported PHEVs in the traffic) were varied from 5 percent to 30 percent with a 5 percent increments. While for the 5% penetration of CVT supported PHEVs at the peak hour volume, the Strategy Three resulted in about 5% energy savings, for the 30% penetration of CVT supported PHEVs, the same strategy (i.e. Strategy Three) resulted in about 31% to 35% energy savings. The Authors also observed a linear relationship between energy savings and penetration rate of CVT supported PHEVs in the case study network.

It should be noted that the authors assumed that accurate signal timing and headway data were provided to PHEVs via the CVT. While it is both difficult and resource-intensive to predict headway information accurately for every vehicle for the entire trip; predicting and providing signal timing information to every vehicle is relatively feasible with the use of existing technology and infrastructure. This suggests that, although Strategy Three performed better than other strategies, Strategy One is a better choice from the implementation perspective.

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TABLE 3: Energy Savings for Penetration

Part 1						
Volume Levels	**Penetration**	**No Strategy**	**Strategy One**	**Strategy Two**	**Strategy Three**
90%	**5%**	4.0%	5.1%	5.1%	5.3%
	10%	8.2%	10.4%	10.4%	10.7%
	15%	12.2%	15.6%	15.5%	15.9%
	20%	16.3%	20.8%	20.7%	21.3%
	25%	20.4%	26.0%	25.8%	26.5%
	30%	24.5%	31.2%	31.1%	31.9%
100%	**5%**	4.2%	5.4%	5.4%	5.6%
	10%	8.6%	11.0%	11.1%	11.3%
	15%	12.9%	16.4%	16.6%	16.9%
	20%	17.3%	22.2%	22.4%	22.8%
	25%	21.5%	27.5%	27.7%	28.3%
	30%	26.0%	33.2%	33.5%	34.2%
110%	**5%**	4.2%	5.3%	5.3%	5.4%
	10%	8.4%	10.7%	10.6%	10.9%
	15%	12.6%	16.0%	16.0%	16.4%
	20%	16.9%	21.5%	21.5%	22.0%
	25%	21.0%	26.7%	26.7%	27.3%
	30%	25.3%	32.3%	32.2%	33.0%
Part 2					
Volume Levels	**Penetration**	**No Strategy**	**Strategy One**	**Strategy Two**	**Strategy Three**
90%	**5%**	4.1%	4.6%	4.5%	4.8%
	10%	8.1%	9.1%	8.9%	9.4%
	15%	12.2%	13.8%	13.4%	14.2%
	20%	16.3%	18.4%	17.9%	18.9%
	25%	20.3%	22.9%	22.3%	23.6%
	30%	24.5%	27.6%	26.8%	28.4%
100%	**5%**	4.3%	5.1%	5.0%	5.2%
	10%	8.6%	10.1%	10.0%	10.4%
	15%	13.0%	15.2%	15.1%	15.7%
	20%	17.3%	20.2%	20.1%	20.9%
	25%	21.6%	25.2%	25.1%	26.1%
	30%	25.9%	30.2%	30.0%	31.2%
110%	**5%**	4.1%	4.6%	4.5%	4.8%
	10%	8.1%	9.1%	8.9%	9.4%
	15%	12.2%	13.8%	13.4%	14.2%
	20%	16.3%	18.4%	17.9%	18.9%
	25%	20.3%	22.9%	22.3%	23.6%
	30%	24.5%	27.6%	26.8%	28.4%

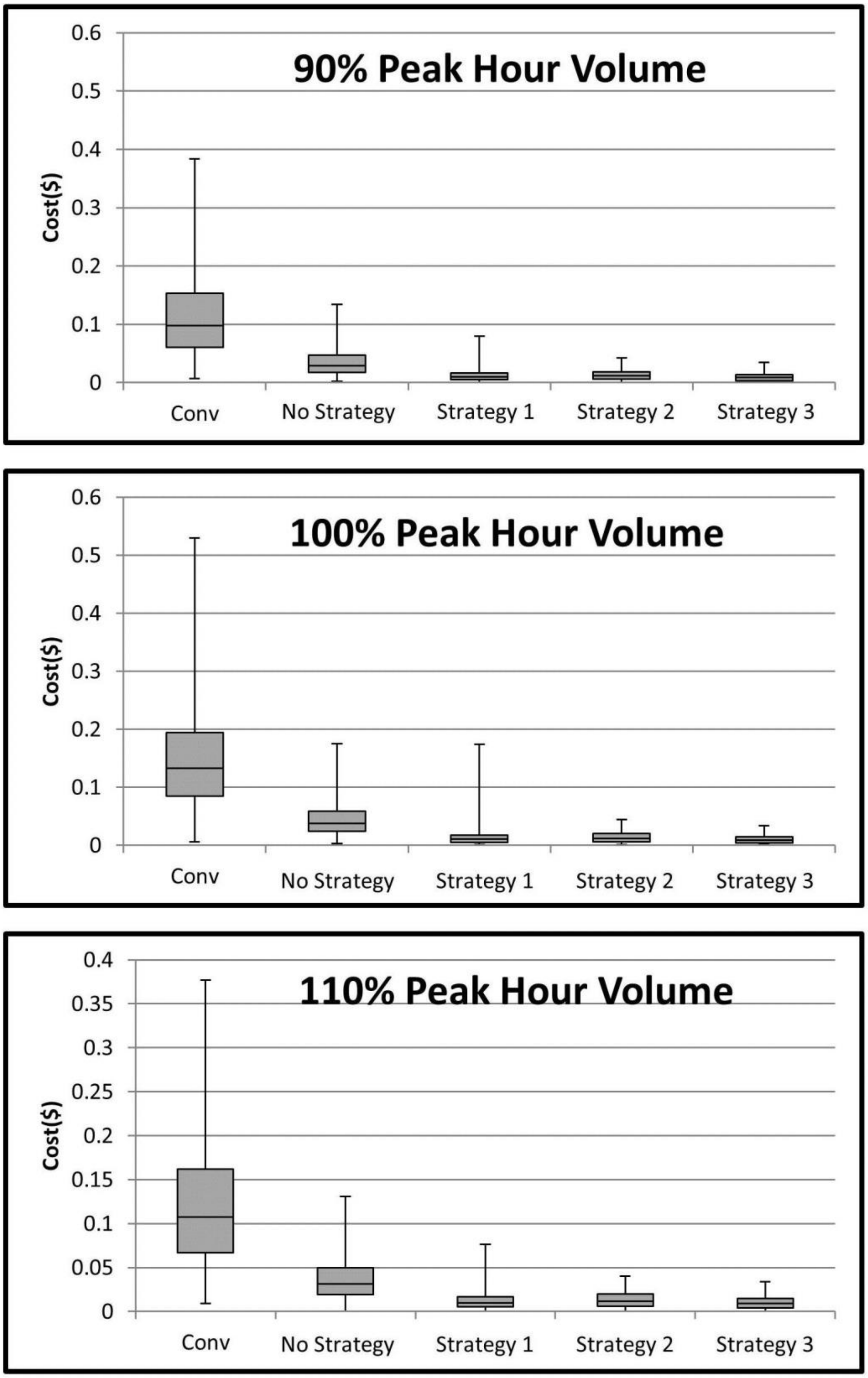

FIGURE 4 Energy Cost in Each Scenario
(*Conv is for conventional vehicle)

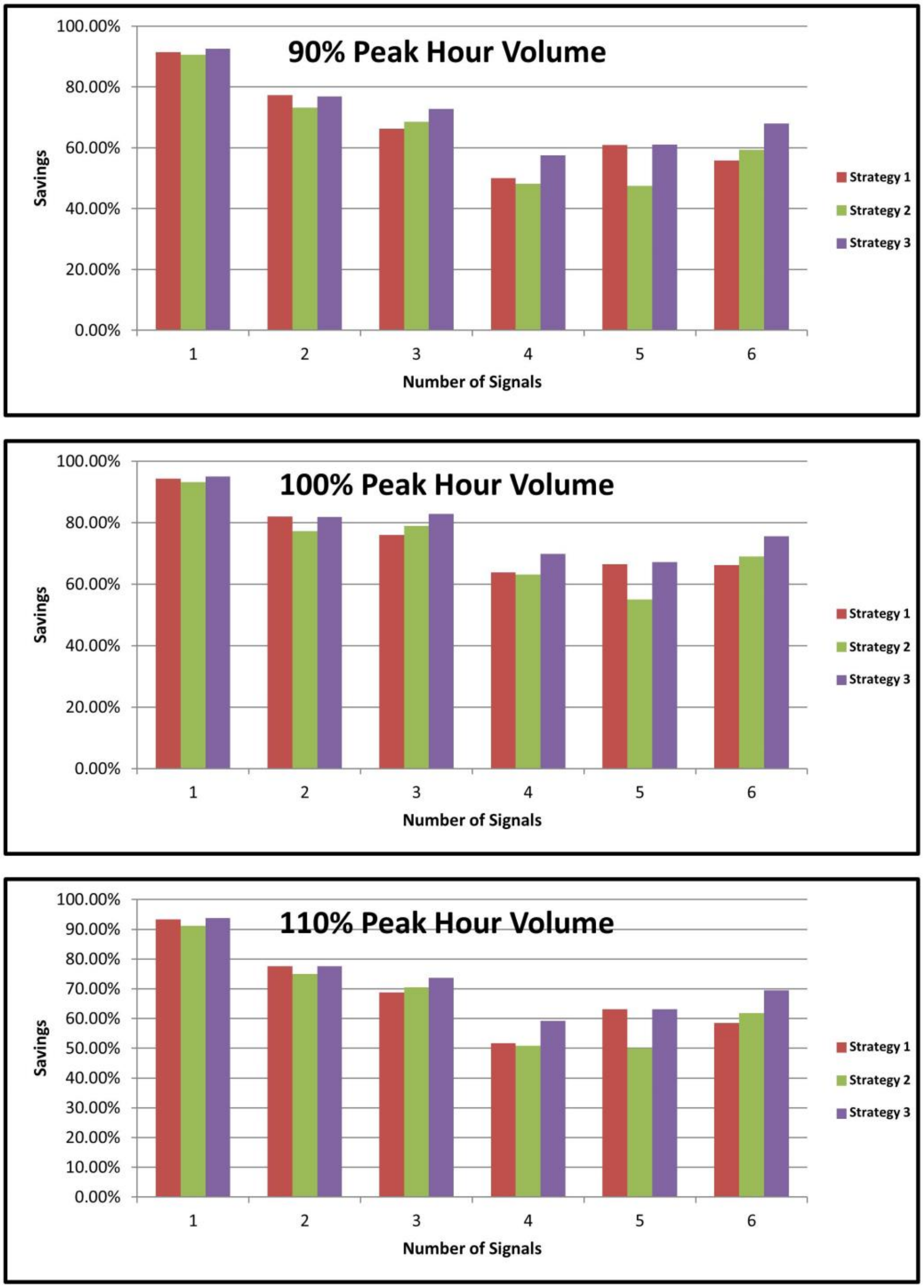

FIGURE 5 Energy Savings vs. Number of Signals

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