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Evolutionary Algorithm Based On-Line PHEV Energy Management System with Self-Adaptive SOC Control

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***Abstract*—The energy management system (EMS) is crucial to a plug-in hybrid electric vehicle (PHEV) in reducing its fuel consumption and pollutant emissions. The EMS determines how energy flows in a hybrid powertrain should be managed in response to a variety of driving conditions. In the development of EMS, the battery state-of-charge (SOC) control strategy plays a critical role. This paper proposes a novel evolutionary algorithm (EA)-based EMS with self-adaptive SOC control strategy for PHEVs, which can achieve the optimal fuel efficiency without trip length (by time) information. Numerical studies show that this proposed system can save up to 13% fuel, compared to other on-line EMS with different SOC control strategies. Further analysis indicates that the proposed system is less sensitive to the errors in predicting propulsion power in real-time, which is favorable for on-line implementation.**

I. INTRODUCTION

In recent years, there has been significant interest in plug-in hybrid electric vehicles (PHEVs) as an effective way to decrease the dependence on fossil fuel and to reduce emissions of greenhouse gases (GHG) and other criteria pollutants from transportation activities [1]. By extending the battery charging capability via external sources (e.g., plugging into an outlet), PHEVs can achieve much better fuel economy than conventional hybrid electric vehicles (HEVs) and have captured 3.5% of U.S. market and 20% of Japanese market in 2012 [2]. However, the fuel efficiency of a PHEV powertrain significantly depends on its energy management system (EMS), characterized by the state-of-charge (SOC) profile of the battery pack.

There have been numerous studies on EMS for PHEVs [3-14]. The rule-based charge depleting/charge sustaining (CD/CS) mode or binary mode strategy is the simplest and the most widely implemented [6], where the PHEV consumes the electricity (i.e., charge depletion) as long as possible before it switches to a charge sustaining (CS) mode when the SOC reaches a pre-set minimum threshold. However, many studies have shown that a blended mode strategy, where the internal combustion engine (ICE) operates in conjunction with the electric motor(s) in response to the power demands, may result in better fuel economy for PHEVs. Examples of blended mode strategies for PHEVs include Equivalent Consumption Minimization Strategy or ECMS [7], Dynamic Programming [8, 9], and Pontryagin's Minimum Principle [10, 11]. Other examples are as follows: Cao et al. validated a control strategy in terms of engine on/off frequency and engine operating condition [12]. Sharer et al. compared different charge depleting strategy options [13]. Banvait et al. studied energy management for PHEVs and developed a rule-based controller in [14]. Wu et al. proposed an efficient optimization strategy based on Mixed Integer Linear Programming (MILP) [1]. Hou et al. designed a range adaptive optimal control strategy for the full-trip energy management [2]. However, most of the aforementioned EMS systems are off-line or not able to operate in real-time.

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The major difficulties of real-time implementation of EMS for PHEVs lie in obtaining a priori knowledge of the system states (e.g., second-by-second speed) as well as the time delay of consecutive intensive computation tasks. To date, very few studies have proposed such on-line implementation. For example, a rule-based real-time controller was developed by extracting the patterns from the powertrain operation under the optimal control [15]. Another real-time suboptimal controller for PHEVs was proposed and compared to an off-line global optimization using Particle Swarm Optimization (PSO) [16]. Qi et al. put forward an evolutionary algorithm based intelligent on-line energy management framework for PHEVs [17], which shows that estimation distribution algorithm (EDA) performs better than other popular evolutionary algorithms such as genetic algorithm (GA) and particle smarm optimization (PSO) in the charge-depleting optimal control. A real-time SOC trajectory builder is designed for on-line EMS in [18] with clustering method.

In this paper, we aim to improve on-line energy management for PHEVs by proposing a self-adaptive SOC control strategy that uses the receding horizon control. The proposed method can adaptively control the use of vehicle battery power or SOC to achieve optimal ICE fuel efficiency in an on-line implementation. More importantly, it does not require trip length (in time) information which is normally assumed to be known in the other existing methods. However, trip length sometimes may vary significantly in certain situations (e.g., an incident occurs). This proposed method is validated and compared with other SOC control strategies on a driving cycle synthesized from real traffic data. For details on trajectory synthesis, please refer to [1].

II. POWER-SPLIT PHEV AND ITS EMS MODELING

There are three types of PHEV powertrain architectures: a) series, b) parallel, and c) power-split (series-parallel) [1]. We focus on the power-split architecture in this study. Fig. 1 depicts the energy flow of a power-split PHEV which includes three major sub-systems: a) internal combustion engine (ICE), b) planetary gear set (PGS), and c) motor/battery.

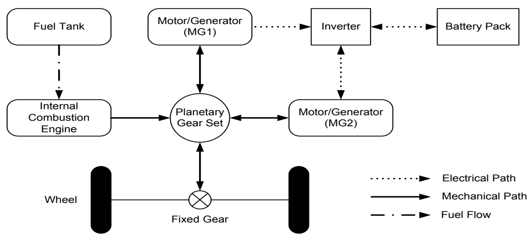

Fig. 1. Power-split plug-in hybrid electric vehicle configuration [1].

A simplified but sufficiently detailed power-split (series-parallel) powertrain model [19] was developed in MATLAB [20] and used in this study.

The optimal charge-depleting control problem for a power-split PHEV can be formulated as a 0-1 Binary Mixed Integer Nonlinear Programming (MINP) as follows:

$$\min \sum_{k=1}^{T} \sum_{i=1}^{N} x(k,i)\, P_i^{eng} / \eta_i^{eng} \tag{1}$$

subject to:

$$\sum_{k=1}^{j} f\left(P_k - \sum_{i=1}^{N} x(k,i) P_i^{eng}\right) \le C \qquad \forall j = 1, \dots, T \tag{2}$$

$$\sum_{i=1}^{N} x(k,i) = 1 \qquad \forall k \tag{3}$$

$$x(k,i) = \{0,1\} \qquad \forall k,i \tag{4}$$

where T is the time span of the entire trip; N is the number of discretized power level for the engine; k is the time step index; i is the engine power level index; C is the gap of the battery pack's state of charge (SOC) between the initial and the minimum; *f*(.) is the function for calculating SOC decrease[1]. P_i^{eng} is the i-th discretized level for the engine power and η_i^{eng} is the associated engine efficiency; and P_k is the driving power demand at time step k.

If the change in SOC (ΔSOC) for each possible engine power level at each time step is pre-calculated, (this task is done by prediction part shown in Fig. 2), then constraint (2) can be replaced by

$$SOC^{ini} - SOC^{max} \le \sum_{k=1}^{j} x(k,i) \Delta SOC(k,i) \le SOC^{ini} - SOC^{min} \qquad \forall i, j = 1, \dots, T \tag{5}$$

where SOC^{ini} is the initial SOC; and SOC^{min} and SOC^{max} are the minimum and maximum of SOC, respectively. Therefore, the problem is reduced to a Mixed Integer Linear Programming (MILP) whose objective is to select the optimal power level for each time step given the predicted information to achieve the best fuel economy along the entire trip.

III. ON-LINE EMS WITH SELF-ADAPTIVE SOC CONTROL

A. *Receding Horizon Control*

As aforementioned, most of the existing strategies for PHEV energy management are off-line. In this work, we formulate the on-line EMS in a receding horizon control framework. Fig. 2 shows the components of the EMS, including information acquisition (from external sources), prediction, optimization, and power split control. In the receding horizon control framework, the entire trip is divided into small segments or time horizons. As shown in Fig. 3, the prediction horizon (*N* sampling time steps) is longer than the control horizon (*M* sampling time steps). Both of these keep moving forward while the system is operating. More specifically, the prediction model is used to predict the power demand at each sampling step (e.g., each second) in the prediction horizon. Then, the optimal ICE power supply for each time step during the prediction horizon is calculated using the predicted information and equations (1) to (5). However, only partial (i.e., within the control horizon) of the computed optimal power-split operation is implemented and the whole process is repeated. It is noted that the prediction and optimization processes for the current prediction horizon are completed during the previous control horizon. Therefore, the selection of *M* and *N* is constrained by the computational tractability of the system, which means the prediction and optimization of *N* seconds should be finished in *M* seconds. According to [17], we choose *M*=10s and *N*=250s. As aforementioned, the focus of this study is to design and implement the optimization component of this on-line EMS. Therefore, the synthesized trip information is used as perfect prediction.

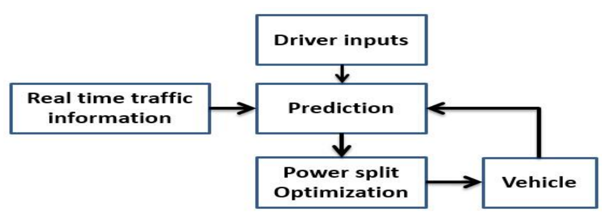

Fig. 2. Flow chart of an online EMS

B. *SOC Control for On-line Optimization*

An appropriate strategy for utilizing vehicle battery power along the trip is critical in achieving optimal fuel economy for PHEVs [21]. More specifically, in the optimization formulation, use of battery power can be determined by the constraints of SOC. In our problem formulation (Eq. (1) to (5)), the major constraint for SOC is defined by Eq.(5), which means at any time step of the trip the vehicle SOC should be in the predefined bound (e.g., between 0.2 and 0.8). This is intended to protect the battery pack from being over-charged or over-discharged. Previous studies indicate that such basic physical constraint on battery use is not sufficient for the optimal on-line power-split control. Instead, it leads to a very quick depletion of the battery pack and the resultant SOC trajectory is much similar to the one from the binary mode control strategy [17]. Hence, additional constraint(s) on battery use (e.g., reference SOC profile) should be introduced to improve the on-line EMS. Fig. 4 presents some example reference SOC profiles and the bound without SOC control.

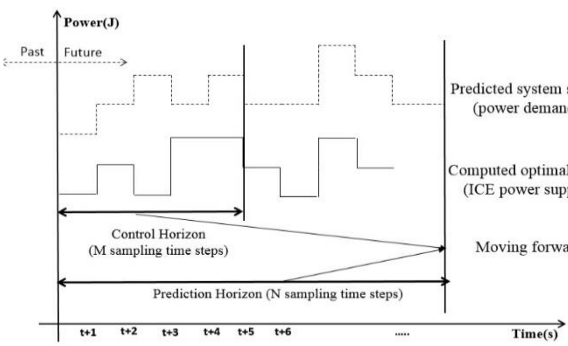

Fig. 3. Time horizons of prediction and control.

For the comparison purpose, three representative reference SOC control bounds with real-time optimal charge-depleting (ROCD) strategies are designed. These reference control bounds are used to provide tighter constraint for the battery use along the trip. More specifically, we choose the following three reference SOC profiles in this study: concave upward, straight line and concave downwards, which are generated by the following equations, respectively:

Concave downward control: (lower bound 1)

$$SOC_i^{min} = \frac{(SOC_{init} - SOC^{min})}{T-(i*M)} * N + SOC_{init} \quad (6)$$

Straight line control :(lower bound 2)

$$SOC_i^{min} = \frac{-(SOC_i^{min} - SOC^{min})}{T} * ((i-1) \cdot M + N) + SOC_{init} \quad (7)$$

Concave upward control :(lower bound 3)

$$SOC_i^{min} = \frac{-(SOC_{i-1}^{end} - SOC^{min})}{T-(i*M)} * N + SOC_{i-1}^{end} \quad (8)$$

Where i is the index of the trip segment or prediction horizon; T is the total time span (in seconds) of the entire trip; SOC_{init} is the initial SOC at the starting point (0.8 in this study); $SOC_i^{min}$is the minimum SOC at the end of i-th prediction segment; SOC^{min} is the allowable minimum SOC (0.2 in this study); N is the length of the prediction horizon; M is the length of control horizon.

It is self-evident that, for example, a concave downward bound (i.e., lower bound 1 in Fig. 4) is more aggressive than a concave upward bound (i.e., lower bound 3 in Fig. 4) in restricting the use of battery at the beginning of the trip. However, a major drawback for these reference control strategies is that they assume that the trip length (in time) is known because it is required for the building of reference SOC profiles as shown in Eq. (6) to (8). Although the trip length may be estimated, in many cases, such information could vary significantly due to the occurrence of unexpected incidents. To overcome this deficiency, a self-adaptive SOC control strategy is needed which will not rely on the knowledge of trip length. This is one of the major contributions of this paper.

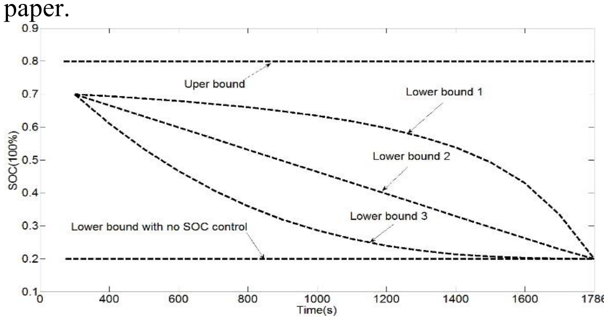

Fig.4. SOC reference control bounds

C. On-line Optimization with Self-adaptive SOC Control

In this study, we propose a novel on-line charge-depleting algorithm with self-adaptive SOC control strategy based on EDA, which is named SA-ROCD. Like most evolutionary algorithms, each candidate solution in the proposed algorithm is encoded as a row vector [22]. The length of the vector is the number of time steps (seconds) within the trip segment. The value of the i-th element of the vector is the ICE power level chosen for that time step. There is a critical assumption that value of each element of the vector follows a univariate Gaussian distribution. This assumption has been proven to be effective in many engineering optimization applications [22], although there could be many other options [23]. Another critical consideration in EDA implementation is the fitness function which is defined as the summation of total ICE fuel consumption for the trip segment (given in the objective function (5)) and a penalty term (the largest possible amount of energy that can be consumed in this trip segment) for those SOC reference control strategies in [17]. However, such definition only takes into account the fuel consumption but not the battery use that is characterized by the SOC trajectory.

In this study, a self-adaptive SOC control strategy is proposed for the EDA-based online energy management system by considering both ICE fuel consumption and battery use in the fitness function, which is defined as follows:

$$f(s) = R_{fuel} + R_{soc} + P \quad (9)$$

where s is the individual for evaluation; R_{fuel} and R_{soc} are the rank of ICE fuel consumption and SOC decrease of individual s in the current population in an ascending order, respectively; P is the added penalty when individual s violates the constraints given in Eq.(2) to (4). The value of the penalty equals the population size (or more), which grantees a non-feasible solution has lower rank than a feasible solution in the ascending order ranking by fitness values. The proposed SA-ROCD algorithm is summarized below.

Algorithm SA-ROCD

Inputs: Predicted power demand at wheel(N time steps); Population size(S);selection ratio α%;Control horizon length(M time steps)

Outputs: Computed optimal control input(M time steps)

1: Initialize a random output I_{best}
2: $P_{current}$ <= Generate initial population randomly
3: While iteration_number ≤ Max_iterations, do
4: For each individual s in $P_{current}$
5: Calculate fuel consumption using eq. (1).
6: Calculate SOC decrease using eq. (5).
7: Obtain the rank index of s: R_{fuel}
8: Obtain the rank index of s: R_{soc}
9: If individual s violates Eqs.(2) to (4)
10: *P=S;*
11: Else
12: *P=0;*
13: End If
14: Calculate the fitness value for s using eq.(9)
15: End For
16: P_{top} <= Select top α% individuals from $P_{current}$
17: E <= Estimate a new distribution from P_{top}
18: P_{new} <= Sample N individuals from built model E
19: Evaluate each individual in P_{new} using line 5 to 14
20: Mix $P_{current}$ and P_{new} to form 2N individuals
21: Rank 2N individuals in ascending order by fitness
22: $P_{current}$<= Select top N individuals
23: Update I_{best} if a better one is identified.
23: Iteration_number ++
24: End While
25: Output I_{best}

Compared to the existing SOC reference control strategies, the proposed self-adaptive SOC control strategy governs the battery power use internally in the optimization process. The SOC control capability is integrated into the optimization process by adding the SOC decrease into the fitness evaluation of the candidate solution that is described by Eq. (9). More importantly, the trip length information is not required any more, which is an obvious advantage over the existing methods.

IV. SIMULATION AND ANALYSIS

A. Synthesized vehicle velocity profile

We herein use the same synthesized velocity trajectory and power demand adapted from [1]. Due to the space limit, we are not providing more details in this paper. But for those interested, please refer to [1] for more information. It should be pointed out that in the practical operation of the on-line EMS depicted in Fig. 2 and 3, the exact vehicle velocity profile cannot be known a priori. But in this study, we treat it as a perfectly predicted trajectory for the purpose of validating the proposed on-line EMS for PHEVs only. For completeness, we evaluate the system performance in the presence of prediction errors in the following.

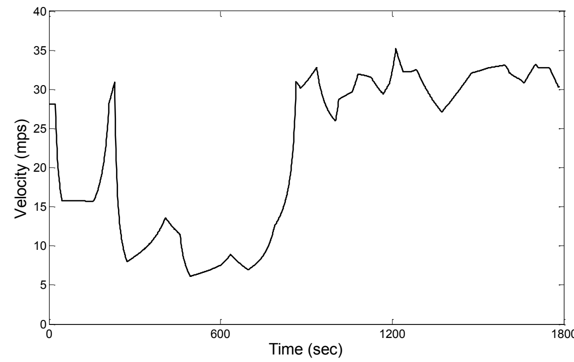

Fig.5. Synthesized velocity trajectory of the example trip.

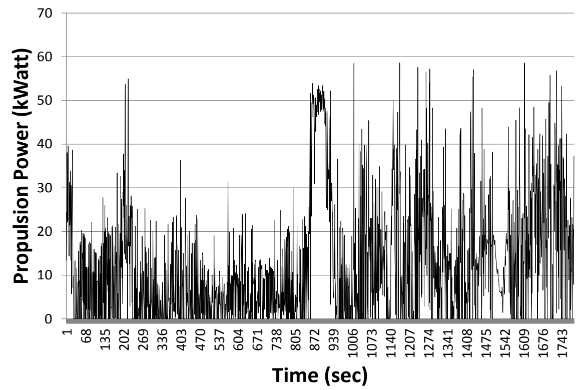

Fig.6. Power demand along the example trip.

B. Comparison of SOC control strategies

To evaluate the proposed self-adaptive SOC control strategy, several strategies are compared with it, including the three SOC reference control strategies mentioned above (i.e., Eq. (6) to (8)), on-line EMS with no SOC control, conventional binary mode control, and the off-line Dynamic Programming (DP) strategy. Table I provides the best fuel cost achieved by each strategy. For clarity, abbreviations for all the compared strategies are also listed in the table.

TABLE I. ABBREVIATIONS OF DIFFERENT SOC CONTROL STRATEGIES COMPARED IN THIS STUDY

SOC control strategies	Abbreviations	Best fuel cost
Binary control	B-C	0.4040 gallon
No SOC control	N-C	0.3887 gallon
Concave downward	C-D	0.3585 gallon
Straight line	S-L	0.3756 gallon
Concave upward	C-U	0.3868 gallon
Self-adaptive SOC control	S-A	0.3515 gallon
Optimal results obtained by DP		**0.3460 gallon**

It is shown in Table I that the proposed S-A algorithm achieves the second best fuel economy (0.3515 gal), which is only 3.6% worse than the theoretical optimum achieved by the off-line global optimizer (DP). And the conventional binary control strategy (B-C) performs the worst. These results can be explained by the shape of the SOC profiles given in Fig.7. For instance, SOC decreases very quickly in the B-C strategy, and reaches the lower bound (i.e., 0.2) at around 1,200 seconds because the use of battery power is always prioritized whenever available. Therefore, ICE has to supply most of the required power after 1,200 sec. This is very similar to the cases of the N-C and C-U strategies where battery power is also consumed aggressively with very loose constraints. On the other hand, the S-L and C-D strategies perform better since their battery power is used more cautiously at the beginning of the trip. These findings are consistent with the conclusion of many other studies [2, 21] in that a smoother distribution of battery power usage along the trip would result in higher fuel efficiency.

A more interesting observation is that, for the proposed S-A strategy, SOC is higher than any other strategies before 900 sec but decreases very quickly after 900 sec. This implies that battery power is used more conservatively before 900 sec, compared to the other strategies. It is also noted that the average velocity before 900 sec is much lower than that after 900 sec; hence, the average power demand is much less before 900 sec (see Fig. 5 and Fig. 6). To further confirm the observation, accumulated fuel consumption curves along the trip are plotted in Fig. 8 for different SOC control strategies. It can be observed that there is an obvious jump of accumulated fuel consumption around 900 sec. The S-A strategy consumes more power from the ICE before 900 sec so that enough battery power is reserved to work together with the ICE for the remaining part of the trip after 900 sec. This implies that the S-A strategy can reserve more battery power in the period of lower power demand for assisting the ICE power supply during the period of higher power demand. In other words, the proposed S-A strategy is able to adjust the battery use in response to the driving conditions along the trip to achieve the optimal ICE fuel efficiency. This also explains why the C-D reference control method (i.e., the power demand of the first half of the trip is much less than that of the second half) performs better than the C-U and S-L methods.

C. *Prediction error analysis*

In the above analysis, we assume that the on-line prediction model can perfectly (i.e., error-free) predict the actual velocity profile along the trip, which is impossible in real-world implementation. To investigate the robustness of the proposed on-line EMS with imperfect prediction of vehicle velocity profile, we evaluate the system performance at different prediction error levels. We simulate the predicted results under different error levels by adding 1%, 3% and 5% of white noise into the original synthesized velocity profile. Fig. 9 shows an example of the contaminated velocity profile with 5% error.

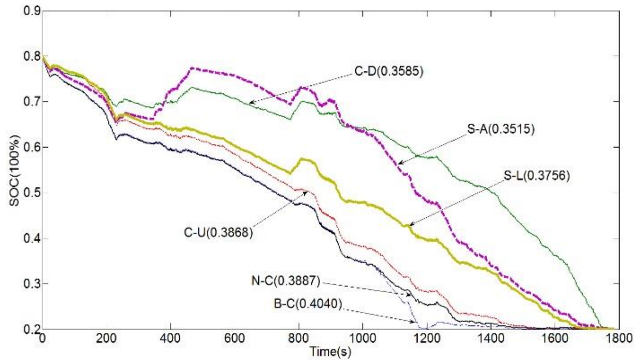

Fig.7. SOC trajectories and total fuel consumption (in US gallon) resulted from different control strategies.

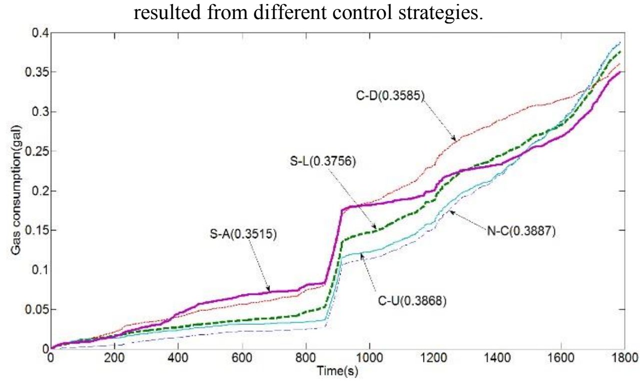

Fig.8. Accumulated fuel consumption curves along the trip for different SOC control strategies (in US gallon).

All the SOC control strategies are evaluated at the different levels of prediction error, and the associated increases in fuel consumption (with respect to the error-free velocity profile) are given in Fig. 10. Based on the performance, the results can be divided into three groups:

Group 1: The N-C strategy exhibits the worst performance since the increase in fuel consumption rises very quickly as the prediction error grows. It is hypothesized that such strategy consumes the battery too aggressively during the early stage of the trip and there is not much reservation for the later stage.

Group 2: The C-U, S-L and C-D strategies are less sensitive to the prediction errors. A potential reason is that the reference control bounds limit the use of battery power. On the other hand, the fixed SOC lower bound impedes the effective adaptation to some extent in the presence of prediction errors.

Group 3: The proposed S-A strategy is the most robust in that it is able to adapt itself to the changes in predicted power demand due to the prediction error. This adaptation ability has been verified in preceding sections.

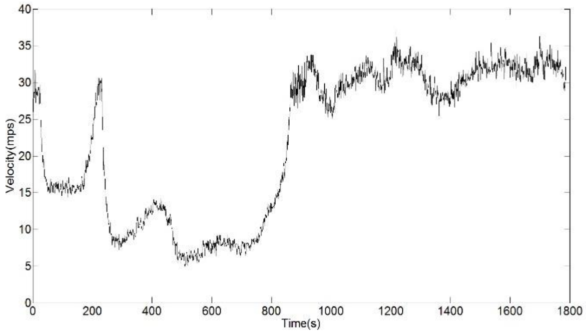

Fig.9. Predicted velocity trajectory with 5% prediction error.

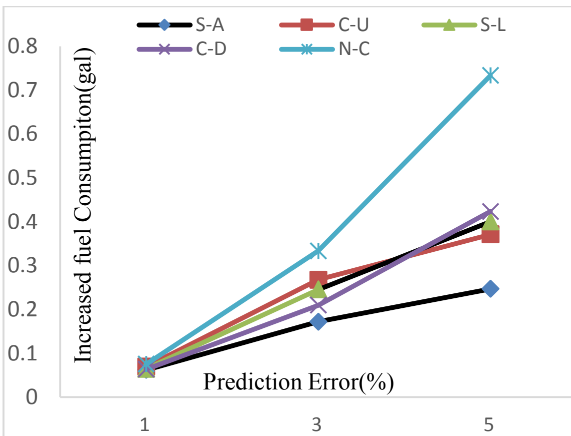

Fig.10. Increased fuel consumptions at different error levels

V. CONCLUSIONS

This paper proposes a novel evolutionary algorithm (EA) based EMS with a self-adaptive SOC control strategy for PHEVs. It has several desirable properties as exhibited by the experimental results. First, the proposed strategy can self-adaptively control the use of battery power (characterized by SOC) to achieve the optimal ICE fuel efficiency for the trip. Such satisfactory performance can be achieved without a priori knowledge of the trip duration, which is a major advantage over other SOC control strategies. In addition, it outperforms other SOC control strategies in terms of fuel consumption for the example trip. Lastly, the proposed strategy is the most robust to prediction errors in vehicle velocity profile among the strategies tested.

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