An Eco-Driving Technique for Energy Aware Driving With an Electric Vehicle

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***Abstract*—Driving habits of individual drivers have shown to have a strong impact on energy consumption and range of electric vehicles. Eco-driving is a popular procedure for improving the range by manipulating multiple factors such as the car speed or providing corrective suggestions related to the route. An optimized eco-driving can be considered for minimizing the energy consumption, taking into account the driving conditions and situations. In this contribution, a driving pattern recognition is considered wherein two indices namely, driving condition index (DCI) and driving situation index (DSI) are used to characterize a certain pattern. Combinations of DCI and DSI are mapped into a representative driving pattern (RDP) matrix. Based on the chosen RDP values, a reference speed for the vehicle is generated and corresponding PI controller parameters tuned within a driver model to realize eco-driving. The eco-driving strategy is optimized for minimization of energy consumption with the help of Pontryagin's minimum principle (PMP) within a constrained action space defined by the DCI and DSI indices. This novel feature allows an event specific optimal solution to be generated rather than a time specific solution. The simulation results prove the efficiency of the optimized eco-driving in preserving the battery energy and charge. It also shows the selection of representative patterns corresponding to actual driving based on DCI and DSI indices.**

I. Introduction

Driving behaviour has a direct impact on sustainability and safety aspects of modern transportation systems. Driving behaviour is a complex outcome of a driver's reaction to the surrounding environment [1]. Mostly, the difference in driving behaviours arise due to variations in acceleration/deceleration patterns which may be primarily due to road and traffic conditions along with other external factors. Driving habits are also strongly related to individual styles as indicated in [2]–[6]. In this context, driving in an energy efficient way can be termed as eco-driving. Eco driving in a more multi-dimensional sense refers to all those decisions which directly or indirectly affect the fuel/energy saving and emissions reduction [7]. As discussed in [7], it includes route selection, modification in driving style, vehicle design specifications, maintenance and judicious use of auxiliary systems like air conditioning etc.

To analyse driving behaviour, most researches focus on collection of speed data through naturalistic driving experiments. In [8]–[10], innovative and comprehensive experiments using driving simulators are considered while in [11]–[13], on board diagnostic scanners (OBDs) are considered. However, most OBDs are unable to capture the traffic data. In [2], smartphones are considered as useful tools to sense and compute data using the crowd sensing technique. The ultimate goals to realizing eco-driving are to model the human driving decisions, predict the future decisions over a certain time horizon, and calculate the optimal control force and velocity profile that minimizes the total energy consumed by the vehicle over the considered time horizon.

Several methods have been discussed to model driving behaviours [14]. Most models employ white box, black box, and grey box architectures. The white box models are derived from theoretical mathematical/physical principles whereas the black box models rely on experimental measurements and are data driven. According to [14], descriptive models such as hierarchical and control loop models describe the driving tasks in terms of a fixed set of actions that a human driver generally takes. It lacks prediction capability and adaption to different driving scenarios. Functional models introduce the influence of uncertainty in driving manoeuvres and hence are more suitable for prediction. In [15], the driving behaviour modelling is performed with Artificial Neural Networks (ANN) and Nonlinear Auto Regressive model with eXogenous Inputs (NARX). An energy-aware personalized joint time-series modeling (PJTSM) approach is considered in [16] with deep recurrent neural networks (RNN). Long short-term memory (LSTM) cell is proposed for motion prediction. Classification based on NN is also considered in [17] whereas recognition

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based on Fuzzy reasoning is considered in [18]. A self-organizing map based NN is considered in [19] to recognize a group of driving patterns.

The main purpose of combining driving pattern recognition (DPR) with energy management strategies is to improve the energy/fuel consumption in electric and hybrid vehicles. In [19], the optimal equivalence factor of an equivalent consumption minimization strategy (ECMS) is adopted based on the recognized pattern. In [20], the performance of a fuzzy logic-based energy management controller is shown to improve when combined with cluster analysis for DPR. The optimal velocity profile can be computed for minimizing the energy consumption over a certain time horizon or over a given route. In [21], a continuous-time convex optimization problem formulation is presented which is solved using sequential quadratic programming (SQP). A multi-objective optimization using weighted sum of objectives is considered in [22]. A single source shortest path algorithm (SSSP) is proposed for eco routing and dynamic programming (DP) for eco driving. A multi-agent reinforcement learning (MARL) is proposed in [23] for eco as well as safe driving, whereas a hybrid approach using model predictive control (MPC) and deep reinforcement learning (DRL) is considered in [24]. Here, MPC is used for finding a local optimal solution for speed control planning whereas DRL is used for a long-term planning based on observed values from MPC. In [25], a simulated annealing algorithm with multiple objectives is used whereas in [26], Pontryagin's minimum principle (PMP) is considered.

It can be concluded from literature that, most optimization techniques when combined with suitable driving control strategies are capable of generating precise eco-driving protocols, however, suitable driving pattern recognition/prediction algorithms are essential for real time control in actual traffic and road conditions. In this contribution, an eco driving strategy is presented for an electric vehicle with a novel two-layer DPR. The DPR relies on the computation of two indices namely, driving condition index DCI and driving situation index DSI. The DCI and DSI of unknown patterns are mapped with known patterns called representative driving patterns (RDPs) to select a certain pattern for the future. The future optimal driving pattern of the EV is decided by the controller parameters which minimize the battery energy consumption for a certain DCI and DSI. In section II the basic concept and system configuration are presented while in section III, the optimized eco-driving strategy is elaborated. Finally in section IV the simulation results are described with discussions and conclusion.

II. Basic Concept and System Configuration

The approach of the proposed DPR has been considered in [27], [28] to analyse the energy consumption traits of vehicles under different driving cycles. In this contribution, it is further extended to allow an eco-driving routine for a battery electric vehicle (BEV). The concept of the proposed DPR is shown in Fig. 1. As a first step, an RDP database with precalculated DCI and DSI values is created. The RDPs are patterns extracted from standard and real cycles representing different driving situations and conditions. Then an unknown driving pattern is classified based on the known RDPs by calculating the DCI and DSI indices over a certain sampling interval. The key idea here is to generate an RDP matrix which combines DCI and DSI indices to define a certain pattern. The choice of the RDP is used to define the future velocity and energy consumption of the battery electric vehicle by selecting the pre-optimized PI controller parameters namely K_p and K_i.

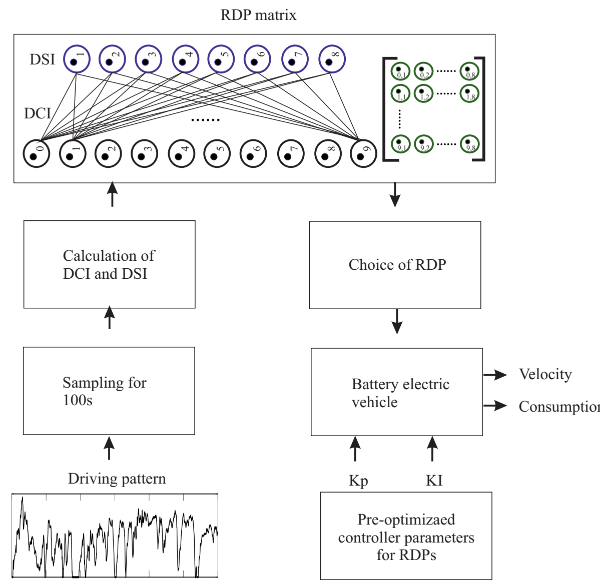


Fig. 1. Concept of proposed DPR

A. Modelling of the battery electric vehicle

The model of a BEV is considered in Matlab/Simulink as shown in Fig. 2 [29]. The driver model uses a PI controller with inputs driving cycle or reference speed and actual vehicle speed. The error $e(t)$ is used to calculate the controller output $u(t)$ as,

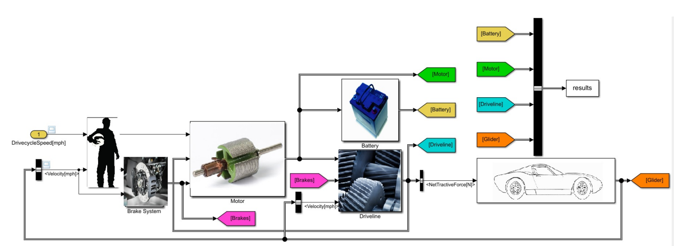


Fig. 2. Battery electric vehicle

$$u(t) = K_p\{e(t) + \frac{1}{T_i}\int_0^t e(\tau)d\tau\}, \tag{1}$$

where K_p represents the proportional gain, and K_i the integral gain. The error $e(t)$ is computed as difference between desired and actual speed

$$e(t) = v_{ref}(t) - v(t), \tag{2}$$

where t is the time interval and τ the integral time. The motor output power is calculated as,

$$P_{motor} = \tau_{motor} * \omega_{motor}, \tag{3}$$

and input power is given as,

$$P_{in,motor} = \tau_{motor} * \omega_{motor} + P_{loss,motor}, \tag{4}$$

where loss in power is calculated based on efficiency maps. An equivalent circuit model of the battery is considered with input power as

$$P_{in,battery} = P_{batt,out} + P_{loss,batt}, \tag{5}$$

where

$$P_{in,batt} = I * V_{oc}, \tag{6}$$

and

$$P_{loss,batt} = I^2 R_{int}. \tag{7}$$

Here I represents the current and R_{int} the internal resistance. The output power is given by

$$P_{batt,out} = IV_{oc} - I^2 R_{int}. \tag{8}$$

The vehicle is modeled based on the equation of forces as

$$F_t = F_i + F_{loss}, \tag{9}$$

where F_{loss} represents the frictional losses due to aerodynamic, rolling and graviatinal forces. The inertial force is given by,

$$F_i = m\frac{dv}{dt}, \tag{10}$$

where v is the vehicle speed, and F_t is the tractive force generated by the prime mover.

The tractive power and energy are calculated as,

$$P_t = F_t * v, \tag{11}$$

and

$$E_t = \int_{t_0}^{t_f} P_t dt, \tag{12}$$

respectively, over the entire drive period t_0 to t_f

B. Driving Pattern Recognition

The driving of human drivers is influenced by multiple factors like road, environmental, and mood conditions. The recognition of driving behaviour is an essential step towards realizing optimal eco-driving. In this contribution, driving behaviour is characterized in terms of DCI and DSI indices to estimate the road and traffic conditions. As a first step, data is collected along a certain route at different times of the day as denoted in Table 1. The differences in the driving patterns along the same route at different times of the day indicate the variation due to traffic. Four characteristic features are considered in this contribution namely the average speed, the maximum acceleration, maximum deceleration, and stop factor. The extraction of characteristic features is done over a sample period of 100 seconds. Certain thresholds are defined

TABLE I
SPECIFICATION OF DATA COLLECTED ALONG A PARTICULAR ROUTE

Data recorded at	Source	Destination	Distance (Km) travelled	Time (Min) taken
Day 1, 09:35 Hrs	12°58'53.2" N, 77°43'35.8" E	12°55'23.1"N, 77°41'06.1" E	12.4 Kms	45 min
Day 1, 17:00 Hrs	12°55'23.1"N, 77°41'06.1" E	12°58'18.0"N, 77°42'55.0" E	14.4 Kms	40 min
Day 2, 09:35 Hrs	12°58'53.2"N, 77°43'35.8 E	12°55'23.1"N, 77°41'06.1" E	12.4 Kms	30 min
Day 2, 18:15 Hrs	12°55'43.1"N, 77°40'47.3" E	12°58'18.0"N, 77°42'55.0" E	12.2 Kms	30 min

for the minimum and maximum boundaries of these values, based on which the DCI and DSI indices are calculated.

The procedure for obtaining the DCI and DSI indices is explained in Fig. 3. First the driving pattern is sampled and the value of average speed (S_{avg}) is computed. Minimum and maximum thresholds are defined based on typical standard data namely $S_{avg,min}$ and $S_{avg,max}$. Then, based on the range of S_{avg}, DCI indices are defined. The maximum positive and negative acceleration (A_{+max} and A_{-min}) along with stop factor (sf) are also computed and again based on pre-defined thresholds, DSI indices are defined. In Fig. 4, the values

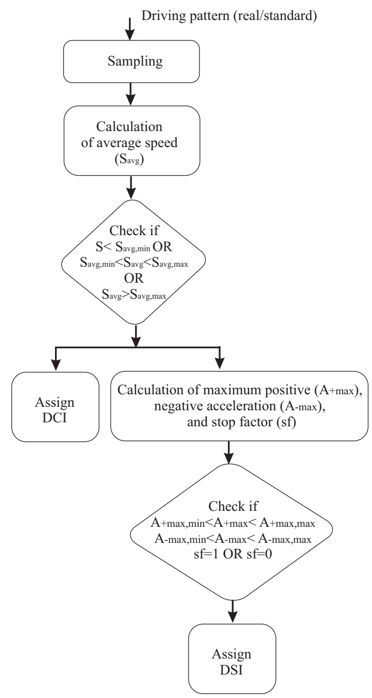
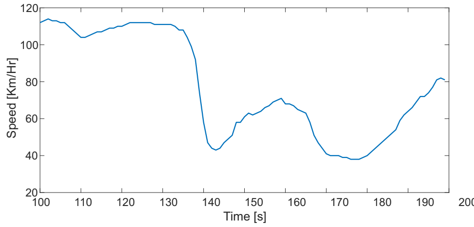


Fig. 3. Calculation of DCI and DSI indices

of characteristic features attained from a 100 second sample of the real driving cycle is shown. A similar procedure of calculating DCI and DSI is followed with patterns extracted from standard cycles. An RDP matrix is created based on the combinations of DCI and DSI indices as shown in Fig. 5. As shown in Fig. 5, the combination of DCI and DSI are mapped



Average speed	76.055 Km/Hr
Maximum acceleration	7 Km/HH
Maximum deceleration	-18 Km/HH
Stop factor	0
DCI	6
DSI	1

Fig. 4. Characteristics features, DCI, and DSI obtained for a driving segment

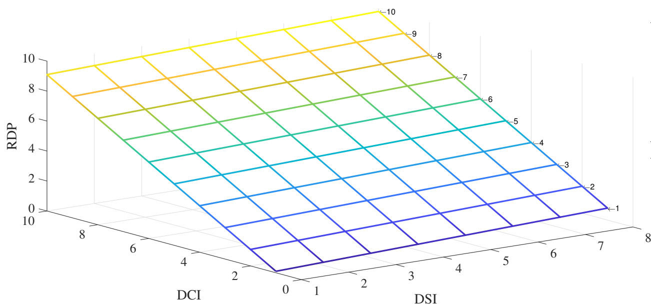


Fig. 5. Creation of RDP matrix

in a matrix known as the RDP matrix. Here, a RDP value of 6.1 indicates DCI value as 6 and DSI value as 1.

III. Eco Driving with BEV

Developing an optimized driving strategy for minimizing the battery energy consumption or sustaining the charge over a longer range is the goal of eco driving as considered in this contribution. The optimal speed control problem is defined to minimize the power over a given time interval t_0 to t_f.

$$\mathrm{J} = \int_{t_0}^{t_f} P_t(\boldsymbol{x}, \boldsymbol{u})dt \tag{13}$$

subject to (14)

$$\begin{cases} \dot{\boldsymbol{x}} = f(\boldsymbol{x}, \boldsymbol{u}) \\ \boldsymbol{x} \in \boldsymbol{\mathcal{X}}, \boldsymbol{u} \in \boldsymbol{\mathcal{U}}(\boldsymbol{x}) \\ \boldsymbol{x}(t_0) = \boldsymbol{x}_0, \quad \boldsymbol{x}(t_f) = \boldsymbol{x_f} \end{cases}. \tag{15}$$

Here,

$$\boldsymbol{x} = \begin{bmatrix} v \end{bmatrix} \text{ and } \boldsymbol{u} = \begin{bmatrix} K_p \\ K_i \end{bmatrix}. \tag{16}$$

The input $u(t)$ or control variables are the PI controller parameters K_p and K_i. Pontryagin's minimum principle (PMP) has been popularly used in [30]–[32] for planning of eco-driving schedules due to its near optimal solutions and real-time applicability. The Hamiltonian H is formulated as [33],

$$H(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda}) = P_t(\boldsymbol{x}, \boldsymbol{u}) + \boldsymbol{\lambda}^T \cdot f(\boldsymbol{x}, \boldsymbol{u}) \tag{17}$$

Here, λ is the co-state variable which is a function of time and $f(\boldsymbol{x}, \boldsymbol{u})$ are the constraint functions. The goal is to find an optimal control policy $\boldsymbol{u}^*$ and corresponding $\boldsymbol{x}^*$ that maximize H.

$$H(\boldsymbol{x}^*, \boldsymbol{u}^*, \boldsymbol{\lambda}) \geq H(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda}) \tag{18}$$

with necessary conditions,

$$\left.\begin{aligned} \dot{\boldsymbol{x}}^* &= \partial H / \partial \boldsymbol{\lambda} \\ \dot{\boldsymbol{\lambda}}^* &= -\partial H / \partial \boldsymbol{x} \\ \boldsymbol{u}^* &= \arg\min_{u \in \mathcal{U}} H(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\lambda}) \end{aligned}\right\} \text{for all } t \in [t_0, t_f]. \tag{19}$$

Here the constraint functions are product of states x_i and associated co-states λ_i. Therefore from equation 17, H can be written as,

$$H(x, u, \lambda) = P_t(x, u) + {\lambda_v}^T v, \tag{20}$$

where

$$\dot{\lambda}_v = -\frac{dH}{dv}. \tag{21}$$

Thus, the objective function of equation 15 can be reformulated as

$$Min\, J = \int_{t_0}^{t_f} \sum_{k=0,n=0}^{k=9,n=8} m\, a_{k,n}\, v_k\, dt, \tag{22}$$

subject to

$$v_{k,avg,min} \leq v_{k,avg} \leq v_{k,avg,max} \tag{23}$$

$$a^+_{k,n,min} \leq a^+_{k,n} \leq a^+_{k,n,max} \tag{24}$$

$$a^-_{k,n,min} \leq a^-_{k,n} \leq a^-_{k,n,max} \tag{25}$$

Here, the state constraints are event discretized to include the DCI and DSI indices. This contraint space includes k index for DCI values and n for DSI values. Thus, the action space includes an optimal solution of each pair of $[dci, dsi]$ as mapped by the RDP matrix. This is further explained in Fig. 6. The first step is to compute the DCI and DSI indices, next, based on the average values of speed $v_{avg}(t)$, maximum positive and negative acceleration a^+ and a^-, to perform the optimization with PMP with $[k, n]$ indices representing DCI and DSI respectively. Then to generate the control actions for the driver model which aims to track the v_{ref} corresponding to the chosen RDP for the BEV model.

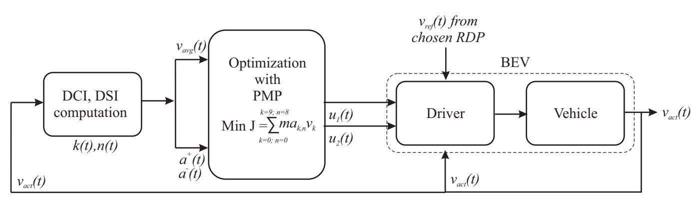


Fig. 6. Optimized eco-driving with PMP

IV. Simulation Results

For a real driving cycle, the DCI and DSI indices are shown in Fig. 7. Here, the DCI index varies between 9 and 3 depending on the variations in average speed of the vehicle. The DSI index however, does not change much. The chosen DSI values are either 1 or 2 depending on whether there has been any stopping or not. A driving segment having DCI value of 6 and DSI value of 2 is shown in Fig. 8. The actual driving shows a gradual acceleration and less braking, leading

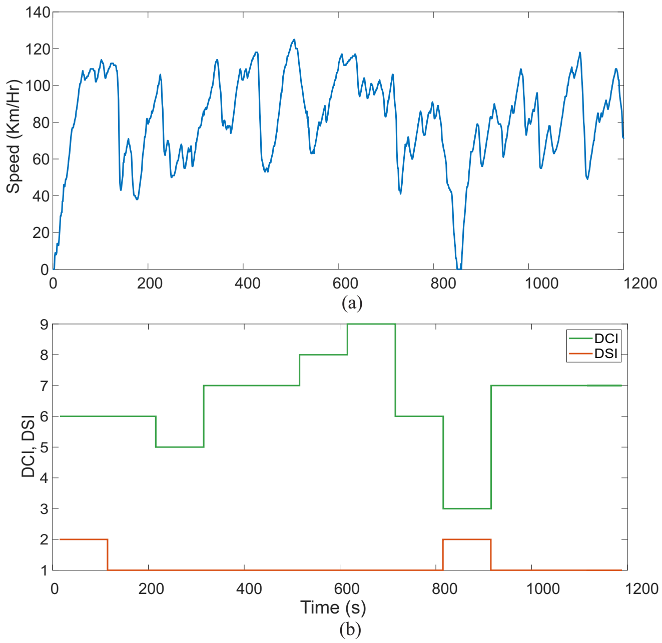


Fig. 7. Driving pattern showing a) speed and b) DCI and DSI indices

to a maximum speed of about 100 Km/Hr. The suggested RDP shows steeper acceleration and deceleration, maintaining the maximum speed below 100 Km/Hr. The corresponding improvement in battery energy and SOC is evident from Fig. 9. Here, based on the chosen RDP, the optimized eco-driving strategy has conserved the SOC and hence more energy can be recovered while driving.

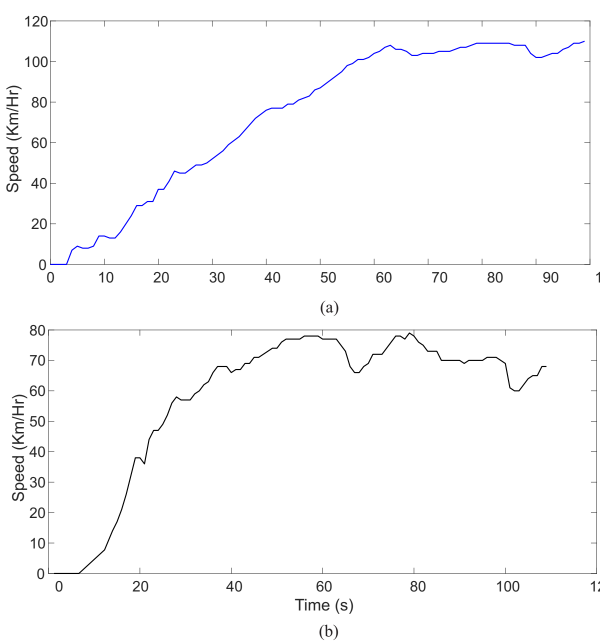


Fig. 8. Driving segment having DCI 6 and DSI 2 showing a) actual driving and b) chosen RDP

The simulation results will be further elaborated in the final version of this paper to include more real world driving cycles

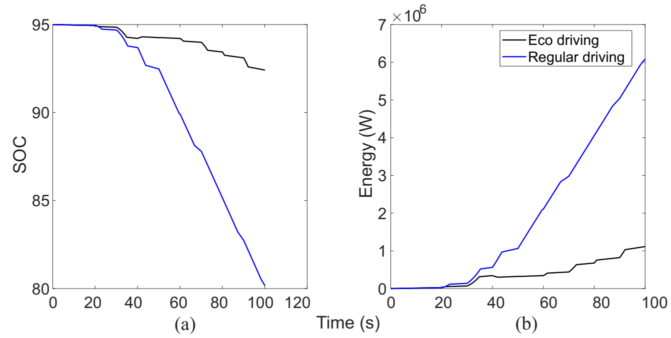


Fig. 9. Driving segment having DCI 6 and DSI 2 showing a) battery SOC b) battery energy for eco and regular driving

and a detailed analysis of the effect of optimization variables on the SOC and energy consumption will be provided.

V. Conclusion

The importance of combining driving pattern recognition (DPR) with energy management of electric/hybrid vehicles has proved to result in improved solutions in terms of optimization objectives. In this contribution an energy-aware, eco-driving strategy is considered for a battery electric vehicle with a novel DPR which relies on computation of two indices: driving condition index (DCI) and driving situation index (DSI). Together these indices are represented in a two dimensional representative driving pattern (RDP) matrix such that corresponding to each combination of DCI, DSI, a unique identifier that is, a driving pattern is defined. These RDPs are formed based on real and standard cycles. An unknown cycle is classified based on the known RDPs and PI controller parameters are tuned corresponding to the RDP which minimizes the energy consumption. The main idea is to formulate an optimization problem within a constrained action space defined by DCI and DSI indices. In other words, for every DCI, DSI, there exists a unique solution and the corresponding RDP which minimizes the energy consumption is used as reference speed to the PI controller. Thus a more event dependent solution is achieved as it is based on the fact that every pattern within a complete cycle maybe similar or different based on the two indices. As a future step, more real world cycles will be used to analyse the effect of proposed DPR and optimization on energy consumption.

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