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IFAC PapersOnLine 54-8 (2021) 83–88

Guaranteed performances for a learning-based eco-cruise control using robust LPV method

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Abstract: In this paper the design of an eco-cruise control system with learning-based agent for automated vehicles is proposed. The control design is based on the robust Linear Parameter-Varying (LPV) framework, in which performance levels of the system can be guaranteed. The motivation of the learning-based agent is to reduce the required on-line computation of the eco-cruise control signal, in which several environmental factors are involved, e.g. the forthcoming terrain characteristics, speed limits. In the proposed method the design of the LPV controller and the selection of scheduling variables are performed in an iterative method. As a result, the proposed system is able to handle the degradation of the learning-based agent, while the performance of the system is guaranteed.

Keywords: automated vehicles, learning and control, robust LPV

1. INTRODUCTION AND MOTIVATION

Novel requirements against the automated vehicle pose complex decision and control challenges to the research teams in the field of the vehicle control design. A possible solution for the adaptation to the varying environment of the vehicle is to build-in learning features in the control systems, with which the economy and comfort performances can be improved. It leads to the concept of eco-cruise control, whose purpose is to design the speed of a vehicle in order to reduce driving energy while keeping traveling time (Sciarretta and Vahidi [2019]). In the design the road information, such as road slopes and speed limits and the local traffic information such as the current speed, the traffic flow and the movement of the surrounding vehicles are taken into consideration. Due to the eco-cruise control the fuel consumption of the vehicle can be significantly reduced, as it has been demonstrated through implementation and test experiments in truck-freeway environment (Gáspár and Németh [2019]).

In the recent years several design methodologies in the field of eco-cruise control systems have been developed, which can provide excellent results theoretically. Most of them are based on on-line optimization processes, which can require high on-line computational demand. Although several methods have been developed to avoid this drawback, it can make difficult to use on-line optimization-based eco-cruise control in practice. In Padilla et al. [2018] a method was proposed to reformulate and discretize the design task by avoiding additional nonconvex terms. A sequential quadratic programming algorithm was provided to find the global optimal solution. The multi-objective optimization problem was handled by using a receding horizon control and evaluated in real experiments in Hellström et al. [2009], Saerens et al. [2013]. Another challenge of the cruise control design is that it can be difficult to describe formally the traveling comfort or the attributes of the human driving.

Learning-based approaches may provide a solution to the previous problems through the joint application of the conventional control (e.g. model-based robust and optimal solutions) and machine-learning-based methods. The role of the learning-based agent in the structure is to learn the a-priori computed optimal control interventions and the human comfort requirements through samples. In case of deep neural networks several optimal solutions, such as the members of a training set are learned offline. In the implementation of the neural networks the vehicle intervention can be performed online. In Bougiouklis et al. [2018] Q-learning algorithm was applied to achieve the optimum speed for the minimization of electric vehicle consumption. Similarly, in Abou-Nasr and Filev [2013] recurrent neural networks were implemented, in which the information about the road slopes was exploited effectively.Deep learning-based eco-driving solution for electric vehicles was presented in Wu et al. [2019], in which information about the surrounding vehicles was also incorporated.

[1] The paper was partially funded by the National Research, Development and Innovation Office (NKFIH) under OTKA Grant Agreement No. K 135512. The research was supported by the Ministry of Innovation and Technology NRDI Office within the framework of the Autonomous Systems National Laboratory Program.
[2] The work of Balázs Németh was partially supported by the János Bolyai Research Scholarship of the Hungarian Academy of Sciences and the ÚNKP-20-5 New National Excellence Program of the Ministry for Innovation and Technology from the source of the National Research, Development and Innovation Fund.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2021.08.585

Despite the promising results on the application of machine-learning methods in the eco-cruise control strategies, a crucial difficulty is the lack of performance guarantees. In eco-cruise control the variation of the velocity concerning to the difference from velocity limit must be bounded, which is a safety performance of the system. It must be guaranteed during the entire route of the vehicle, even if the fuel consumption is increased temporarily. Thus, an important challenge in control theory is how performance levels of machine-learning-based agent can be quantified and guaranteed, which motivates the formulation of several new control problems. As an example, neural networks have been used to approximate the output of the model predictive control through a training process on the optimal solutions of various scenarios in Hertneck et al. [2018]. It resulted in the computational time reduction of the control signal, while the stability and constraints are guaranteed.Repetitive learning approach is presented in Rosolia and Borrelli [2018]. The goal of the method is to construct recursively terminal set and terminal cost from state and input trajectories of previous iterations. The feasibility and the nondecreasing property of the performances are guaranteed, because the learning feature is incorporated in the predictive optimal framework, such as the learning of the terminal set and the terminal cost through iterations. However, the method is incompatible with the distinct machine-learning structures, which is a disadvantage of the method. Since learning methods can be used effectively in the design problem of the eco-cruise control, it may be fruitful to take them to the part of the control without significant modification. The motivation of this paper is to provide a design framework for the problem of performance guarantees in eco-cruise control systems, in which the machine-learning-based agent can be designed independently.

The method proposes an design method for eco-cruise control in which machine-learning-based agent for the computation of the optimal velocity profile can be incorporated. The design process is based on the robust Linear Parameter-Varying (LPV) framework, with which the selected velocity performance of the eco-cruise control can be guaranteed. The motivation behind the robust LPV formalism is flexibility, which may be achieved through the scheduling variable. In the method control the force intervention of the vehicle is expressed as a multiplication of the LPV controller output and the scheduling variable, together with an known additive disturbance. By using the scheduling variable and the disturbance a wide range of machine-learning outputs can be covered. The principle of the method is that a robust LPV control is designed whose output signal is equivalent to the output signal of the machine-learning-based control in a predefined domain. If the LPV control can be designed, the performance level of the machine-learning-based control inside of the domain is achieved. Outside of the predefined domains the performance level of the control system is equivalent to the guaranteed performance level of the LPV control. The most important advantage of the proposed method is that it is independent of the structure of the applied machine-learning technique. Moreover, the resulted eco-cruise control architecture requires significantly less on-line computation effort compared to the classical predictive solutions, which requires expensive on-line optimization processes.

The paper is organized as follows. Section 2 proposes the concept of the method, the control rule and the structure of the control architecture are presented. The iterative design of the LPV control together with the optimization of the scheduling variable and the known disturbance domains are proposed in Section 3. In Section 4 an optimization-based selection method of the values for the scheduling variable and the known disturbance are provided. The effectiveness of the method for eco-cruise control is presented in Section 5, while the consequences are summarized in Section 6.

2. FUNDAMENTALS OF THE CONTROL DESIGN CONCEPT

The basic idea of the control strategy is to design a model-based controller, which approximates the output of the learning-based agent. Although the learning-based agent is able to control the vehicle individually, due to the problems in performance guarantees it can be disadvantageous. Nevertheless, the performance of the model-based controller is guaranteed in theory and the performance degradation of the learning-based-agent is avoided through the overriding of its output. In this paper the LPV framework has been used to design the model-based controller.

The output of the machine-learning-based control is represented as

$$u_L = \mathcal{F}(y_L) \tag{1}$$

where y_L vector contains the inputs of the controller with m_L elements and $\mathcal{F}$ represents the machine-learning-based controller itself. In the present eco-cruise control problem $\mathcal{F}$ is a neural network, which is fitted on the control force intervention F_l of a multi-objective predictive optimal controller, in which the road and traffic conditions on the forthcoming road section are considered (Gáspár and Németh [2019]). The numbers of the hidden layers and the neurons are selected by using the so-called k-fold cross validation technique (Arlot and Celisse [2010]) and the Levenberg-Marquardt algorithm is used for training purposes (Hagan et al. [1996]). Thus, y_L contains the road inclinations and velocity limitations in distinct segment points on the predicted horizon, while u_L is the actual longitudinal control force.

Moreover, the control signal u_K is defined, which is the output of a robust LPV controller, such as

$$u_K = \mathcal{K}(\rho_K, y_K) \tag{2}$$

where $\mathcal{K}$ represents the LPV controller and y_K is the vector of the measured signals with m_K elements. In (2) $\rho_K \in \varrho_K$ vector contains the scheduling variable of the controller, which is derived from the following control rule.

The fundamental assumption of the proposed method is that the control input signal of the system u can be expressed in a linear form of u_K, under predefined conditions. The relationship between u, u_K and u_L with the conditions is formed as

$$u = \rho_L^* u_K + \Delta_L^* := u_L, \text{ if } \quad \rho_L^* \in \varrho_L, \ \ \Delta_L^* \in \Lambda_L, \tag{3}$$

where ρ_L^* and Δ_L^* are time-dependent weighting signals. $\varrho_L = [\rho_{L,min}; \rho_{L,max}]$, $\Lambda_L = [\Delta_{L,min}; \Delta_{L,max}]$ represent domains in (3), where $\rho_{L,min}$, $\rho_{L,max}$, $\Delta_{L,min}$, $\Delta_{L,max}$ are scalars. The sets of the domains are denoted by ϱ_L, Λ_L.

If both conditions of (3) are guaranteed, the control input of the system u approximates u_L through the appropriate selection of ρ_L^* and Δ_L^*. But, if $\rho_L^* \notin \varrho_L$ or $\Delta_L^* \notin \Lambda_L$, the variables ρ_L^*, Δ_L^* are limited with the boundaries of ϱ_L and Λ_L during the computation of the control signal u. In this case u can significantly differ from u_L. The general control rule, which contains both scenarios is formed as

$$u = \rho_L u_K + \Delta_L, \tag{4}$$

where

$$\rho_L = \min\Big(\max\left(\rho_L^*; \rho_{L,max}\right); \rho_{L,min}\Big), \tag{5a}$$

$$\Delta_L = \min\Big(\max\left(\Delta_L^*; \Delta_{L,min}\right); \Delta_{L,max}\Big). \tag{5b}$$

The relations (5a)-(5b) guarantee that $\rho_L \in \varrho_L$ and $\Delta_L \in \Lambda_L$.

The architecture of the proposed control strategy is shown in Figure 1. In the eco-cruise control process the machine-learning-based agent and the robust LPV controller are taken into consideration, u_L and u_K are computed simultaneously. The role of the control force F_l optimization block is to select ρ_L, Δ_L and to generate u based on the rule (4). The selection of ρ_L, Δ_L is based on a constrained quadratic optimization procedure, which is detailed in Section 4. Although the eco-cruise control strategy contains an on-line optimization process, it requires significantly less computation effort than the classical predictive eco-cruise control methods.

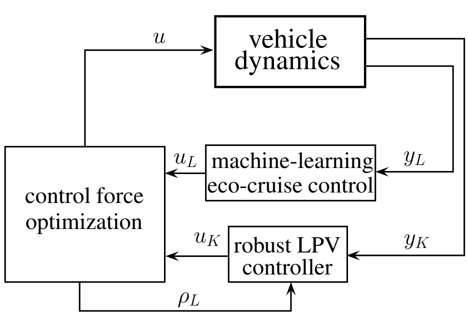


Fig. 1. Scheme of the eco-control strategy

The architecture presents the main idea of the proposed concept. The minimum performance level of the eco-cruise control from the aspect of the velocity variation is determined by the LPV controller in the entire operation domain of the system. But, inside of the domains ϱ_L, Λ_L the performance level is enhanced through machine-learning-based control. Through the proposed control strategy the advantages of machine-learning-based control can be achieved, while its drawback, such as performance degradation in some scenarios, is eliminated through the guaranteed minimum performance level.

3. ITERATIVE DESIGN OF THE LPV CONTROL

The representation of the system is formed in the following control-oriented state-space representation as

$$\dot{x} = Ax + B_1 w + B_2 u, \tag{6}$$

where x represents the state vector, w vector contains the disturbances and u vector incorporates in the control input. A, B_1, B_2 are matrices in the system representation. In the design of the eco-cruise control system the simplified longitudinal model of the vehicle is applied (Gáspár and Németh [2019]) as

$$m\ddot{\xi} = F_l + F_d, \tag{7}$$

where m is the mass of the vehicle. The state vector is $x = \begin{bmatrix}\dot{\xi} & \xi\end{bmatrix}^T$, where ξ represents the longitudinal motion of the vehicle and $w = F_d$ contains the longitudinal disturbance force and $u = F_l$ involves the longitudinal control force.

The goal of the design is to derive the robust controller which guarantees a minimum performance level for the closed-loop system, considering the predefined control rule (4). The output of the controller u_K is used in the expression $u = \rho_L u_K + \Delta_L$. Therefore, the state-space representation of the system (6) is reformulated through the relationship between u and u_K as

$$\dot{x} = Ax + B_1 w_K + B_2(\rho_K) u_K, \tag{8}$$

where the disturbance vector w_K of the state-space representation (8) is composed as $w_K = [w \;\; \Delta_L]^T$ and the matrices are $B_1 = [B_1 \;\; B_2]$ and $B_2(\rho_K) = B_2 \rho_L$. (8) relation contains ρ_L in $B_2(\rho_K)$, which is selected as a scheduling variable $\rho_K = \rho_L$. Thus, the system is transformed to an LPV representation.

In the robust LPV framework the role of the controller is to guarantee a minimum performance level (Wu et al. [1996]). Performance z_K of the closed-loop system with $\mathcal{K}(\rho_K, y_K)$ is expressed through the control inputs u and the existing disturbances w in a general form as

$$z_K = C_2 x + D_{21} w + D_{22} u. \tag{9}$$

In the eco-cruise control problem two performances are defined. First, it is necessary to minimize the velocity tracking error $|\dot{\xi}_{ref} - \dot{\xi}|$, where $\dot{\xi}_{ref}$ is the reference velocity. In the proposed control $\dot{\xi}_{ref}$ is selected as the maximum velocity limit on the road section. The second performance is the minimization of $|u|$. Similarly to the state-space representation (6)-(8), the performance equation (9) through $u\rho_L u_K + \Delta_L$ is also reformulated as

$$z_K = C_2 x + D_{21} w_K + D_{22}(\rho_K) u_K, \tag{10}$$

where the matrices are $D_{21} = [D_{21} \; D_{22}]$, $D_{22}(\rho_K) = D_{22}\rho_L$.

Similarly to z_K, the measured outputs y_K can be expressed in the form of

$$y_K = C_1 x + D_{11} w_K + D_{12} u_K, \tag{11}$$

where the matrices of (11) are $D_{11} = [D_{11} \; D_{12}]$, $D_{12}(\rho_K) = D_{12}\rho_L$. In the eco-cruise control design the measured signal is defined as the velocity tracking error $y_K = \dot{\xi}_{ref} - \dot{\xi}$.

The quadratic LPV performance problem is to choose the parameter-varying controller $\mathcal{K}(\rho_K, y_K)$ in such a way that the resulting closed-loop system is quadratically stable and the induced $\mathcal{L}_2$ norm from the disturbance w_K to the performances z_K is less than the value γ (Wu et al. [1996]). The minimization task is the following:

$$\inf_{\mathcal{K}(\rho_K,y_K)} \sup_{\rho_K \in \varrho_K} \sup_{\substack{\|w_K\|_2 \neq 0,\\ w_K \in \mathcal{L}_2}} \frac{\|z_K\|_2}{\|w_K\|_2}. \tag{12}$$

The existence of a controller that solves the quadratic LPV γ-performance problem can be expressed as the feasibility of a set of LMIs, which can be solved numerically. Finally, the state-space representation of the LPV control $\mathcal{K}(\rho_K, y_K)$ is constructed (Wu et al. [1996], Sename et al. [2013]), which leads to the control input u_K. The input signal u_K is incorporated in the computation of u together with the selection of ρ_L, Δ_L. The control rule results in that the minimum performance level of the closed-loop system is determined by $\mathcal{K}(\rho_K, y_K)$.

Iterative control design and domain selection

The optimization problem (12) shows that the resulted controller depends on the domains ϱ_K, Λ_K. If the ranges of the domains are selected small, u_L is often saturated by the boundaries of the domains, see (5). But, if the ranges have insufficiently high values, the resulted LPV controller can be conservative and the tracking performance level is reduced. Thus, it is necessary to find a balance in the selection of the domain, which is based on an iteration process.

The goal of the iteration is to fit the velocity of the vehicle $\dot{\xi}$ on the velocity of a reference vehicle $\dot{\xi}_L$, which has the control input u_L. In this concept the reference vehicle has the ability to move by the eco-cruise controlled strategy. Through the optimization the domains are selected to approximate the motion of the vehicle to the motion of the reference vehicle as

$$\min_{\rho_{L,min},\, \rho_{L,max}} \sum_{j=1}^{N} |\dot{\xi}_{L,j} - \dot{\xi}_j|, \tag{13}$$

where j expresses the time step and N is the length of a given scenario. Using the results of (13) the boundaries of the domain $\Lambda_L = [\Delta_{L,min}; \Delta_{L,max}]$ are computed based on the rule (4) as

$$\Delta_{L,min} = \min\left(u_L - \rho_{L,min} u_K\right), \tag{14a}$$

$$\Delta_{L,max} = \max\left(u_L - \rho_{L,min} u_K\right). \tag{14b}$$

The solution of the optimization problem (13) begins with domains with high ranges, which are reduced through the following iteration process.

(1) The domains $\varrho_L = [\rho_{L,min}; \rho_{L,max}]$ and $\Lambda_L = [\Delta_{L,min}; \Delta_{L,max}]$ are selected high in the first step, which can result in a conservative LPV controller.
(2) The LPV control with the selected domains is designed using (12).
(3) The closed-loop system with the incorporation of the designed $\mathcal{K}(\rho_K, y_K)$ and the domains ϱ_L, Λ_L are analyzed through various scenarios. It yields in the signals $\dot{\xi}_{ref}$ and $\dot{\xi}$, from which the cost in (13) for the scenario is calculated.
(4) Due to the results of the scenarios the boundaries are modified to reduce the cost function of the optimization problem (13). The setting of the optimization variables can be performed through e.g. simplex search or trust-region-reflective methods, see Lagarias et al. [1998], Coleman and Li [1996].
(5) The LPV design, the scenarios and the evaluation (steps 2-4) are performed until the minimum of (13) is reached.

The results of the entire iteration process are the robust LPV controller $\mathcal{K}(\rho_K, y_K)$ and the domains ϱ_L, Λ_L. The optimization processes (12) and (13), together with the design of $\mathcal{F}$ are performed off-line, with which the quantity of the on-line computation is significantly reduced, compared to the classical optimal eco-cruise control strategies.

4. SELECTION OF THE VALUES FOR SCHEDULING VARIABLES AND MEASURED DISTURBANCE

The selection strategy of ρ_L and Δ is based on the relation between u_L and u_K, see (4). During the selection of ρ_L, Δ_L various criteria must be guaranteed, while the constraints $\rho_L \in \varrho_L$, $\Delta_L \in \Lambda_L$ are satisfied.

(1) The control input u must be as close as possible to u_L, which leads to the objective
$$|u - u_L| \to min. \tag{15}$$
Through (15) the traction force intervention of the eco-cruise control system is close to the machine-learning-based intervention, which is required if the performance of the machine-learning-based control is acceptable.
(2) The control signal u must be in the set of the robustness, which can be expressed as
$$\Delta = u - u_K = (\rho_L - 1)u_K + \Delta_L. \tag{16}$$
The robustness of the closed-loop system is guaranteed, if Δ is bounded with a predefined value Δ_{max}, which is incorporated in the robust control design. Thus, the following constraint during the selection of ρ_L, Δ_L must be satisfied:
$$|(\rho_L - 1)u_K + \Delta_L| \leq \Delta_{max}. \tag{17}$$
The criterion (17) can be transformed as
$$\begin{bmatrix} -u_K & -1 \\ u_K & 1 \end{bmatrix} \begin{bmatrix} \rho_L \\ \Delta_L \end{bmatrix} \leq \begin{bmatrix} \Delta_{max} - u_K \\ \Delta_{max} + u_K \end{bmatrix} \tag{18}$$
(3) In the scenarios, when u_L is unacceptable, the intervention $u_{K,i}$ is preferred. The selection of $\rho_L = 1, \Delta_L = 0$ guarantees the criterion (17) and $u = u_K$ is achieved, which leads to the objective
$$|\rho_L - 1| \to min, \tag{19a}$$
$$|\Delta_L| \to min. \tag{19b}$$

The formulated objectives and constraints can be transformed into the following optimization task, whose results are ρ_L, Δ_L. The objective function contains (15) and (19), such as

$$Q_1(u - u_L)^2 + Q_2\left((\rho_L - 1)^2 + \Delta_L^2\right), \tag{20}$$

which can be transformed to a quadratic optimization form through the relation $u = \rho_L u_K + \Delta_L$. Using the constraint (17) and the bounds on ρ_L, Δ_L, the following optimization problem is yielded

$$\min_{\rho_L,\Delta_L} \begin{bmatrix}\rho_L\\ \Delta_L\end{bmatrix}^T \beta \begin{bmatrix}\rho_L\\ \Delta_L\end{bmatrix} + \omega^T \begin{bmatrix}\rho_L\\ \Delta_L\end{bmatrix} \tag{21a}$$

subject to

$$\begin{bmatrix}-u_K & -1\\ u_K & 1\end{bmatrix} \begin{bmatrix}\rho_L\\ \Delta_L\end{bmatrix} \leq \begin{bmatrix}\Delta_{max} - u_K\\ \Delta_{max} + u_K\end{bmatrix} \tag{21b}$$

$$\rho_L \in \varrho_L \tag{21c}$$

$$\Delta_L \in \Lambda_L, \tag{21d}$$

where

$$\beta = \begin{bmatrix}Q_1 u_K^2 + Q_2 & Q_1 u_K - Q_2\\ Q_1 u_K - Q_2 & Q_1 + Q_2\end{bmatrix}, \tag{22a}$$

$$\omega^T = \begin{bmatrix}-2Q_1 u_L u_K\\ -2Q_1 u_L\end{bmatrix}. \tag{22b}$$

The weights Q_1, Q_2 have high importance to guarantee the priority between (15) and (19). Since the (15) leads to $u \to u_L$, while (19) results in $u \to u_K$, both criteria cannot be satisfied simultaneously. Criterion (15) has importance, when u_L is acceptable and (19) has relevance in the further scenarios. Focusing on the problem of eco-cruise control system, u_L is acceptable, when the safety criteria on the velocity profile of the vehicle is guaranteed, such as

$$\dot{\xi} \in [\dot{\xi}_{min}; \dot{\xi}_{max}], \tag{23}$$

where $\dot{\xi}$ is the velocity of the vehicle. $\dot{\xi}_{min}, \dot{\xi}_{max}$ values represent the domain, in which the velocity of the vehicle is acceptable. These values are determined by the velocity limits on the road sections, from which $\dot{\xi}$ can vary in a predefined range.

The criterion (23) is built in the selection of Q_2 by the following way

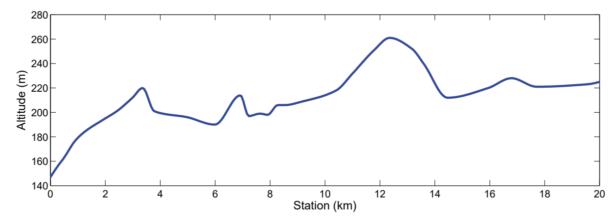
$$Q_2 \triangleq \left\{ \begin{array}{ll} 0, & \text{if } \dot{\xi} \in [\dot{\xi}^*_{min}; \dot{\xi}^*_{max}] \\ Q_2^* \frac{\dot{\xi}^*_{min} - \dot{\xi}}{\dot{\xi}^*_{min} - \dot{\xi}_{min}}, & \text{if } \dot{\xi} \notin [\dot{\xi}_{min}; \dot{\xi}^*_{min}] \\ Q_2^* \frac{\dot{\xi} - \dot{\xi}^*_{max}}{\dot{\xi}_{max} - \dot{\xi}^*_{max}}, & \text{if } \dot{\xi} \notin [\dot{\xi}^*_{max}; \dot{\xi}_{max}] \\ Q_2^*, & \text{if } \dot{\xi} \notin [\dot{\xi}_{min}; \dot{\xi}_{max}] \end{array} \right\}, \tag{24}$$

where $\dot{\xi}^*_{min} > \dot{\xi}_{min}$ and $\dot{\xi}^*_{max} < \dot{\xi}_{max}$ are design parameters and Q_2^* is the maximum value of Q_2. Q_2^* must be selected to be significantly higher than Q_1, which guarantees that has high priority against (15) in unacceptable scenarios (19).

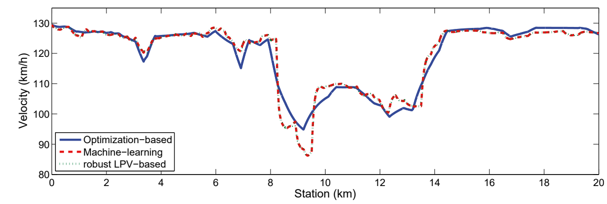
5. ILLUSTRATION OF THE ITERATIVE DESIGN

In this section the effectiveness of the proposed method for eco-cruise control is illustrated through simulation examples. In the simulations three control strategies are compared, such as the optimization-based eco-cruise control (Gáspár and Németh [2019]), the machine-learning-based control $\mathcal{F}$ with input u_L and the proposed robust LPV-based control strategy. The training set for $\mathcal{F}$ and the scenarios for the iterative LPV control design have been generated by vehicle dynamic simulations on various European freeway sections. The dynamic model of the vehicle is based on the parameters of a conventional passenger car. The aim of the examples is to show that the proposed method is able to guarantee that the velocity profile of the vehicle is inside of a predefined range, even at the performance degradation of the machine-learning-based control.

Figure 2 shows an example on a section of the Hungarian freeway M1 between Budapest and Vienna with $90km/h$ velocity limitations between $8.2km \dots 13.5km$. This route is contained by the training set of $\mathcal{F}$. The velocity signals in Figure 2(b) illustrates that the training process and also the iteration process have been successful. The resulted velocity profile with the machine-learning-based control and with the LPV-based control are close to the velocity with the original eco-cruise control, see Figure 2(b). It resulted that the difference in the driving energy of the original eco-cruise control and the proposed control strategy is only 1.75%. Thus, the proposed control strategy is able to achieve the same performance level in the velocity selection with significantly less on-line computation requirement.



(a) Terrain characteristics



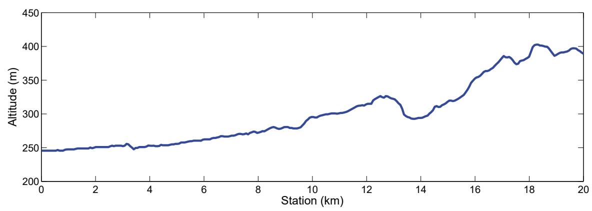
(b) Velocity profiles of the vehicle

Fig. 2. Simulation scenario on the freeway section of M1

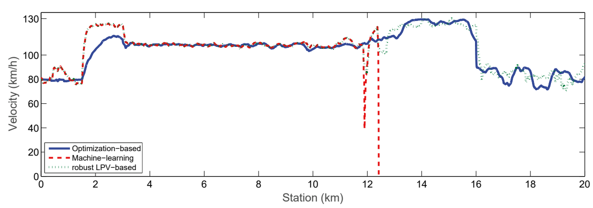
Another example on the effectiveness of the LPV-based control strategy is illustrated in Figure 3. In this scenario the vehicle is driven along a section of the French freeway A36 between Mulhouse and Belfort (Figure 3(a)) with varying velocity limitations between $80km/h \dots 130km/h$. In the simulation $\dot{\xi}_{min}, \dot{\xi}_{max}$ are selected as $-20\%, +5\%$ variation compared to the actual velocity limit. This scenario contains several road sections, which are out of the training set of $\mathcal{F}$. Therefore, the velocity profile with the machine-learning-based control can significantly differ from the velocity with the original eco-cruise control. It also results in critical situations, when the vehicle is stopped on the freeway (Figure 3(b)) due to unacceptable u_L, see Figure 3(c) around $12km$. Nevertheless, the proposed robust LPV-based control strategy is able to handle the performance degradation via the appropriate selection of Q_2. Figure 3(b) shows that the velocity with the robust LPV-based control is close to the velocity with the optimization-based control during the entire simulation. The significant reduction of the velocity can be avoided through the limitation of Δ_L and ρ_L, see Figure 3(d)-(e).

6. CONCLUSIONS

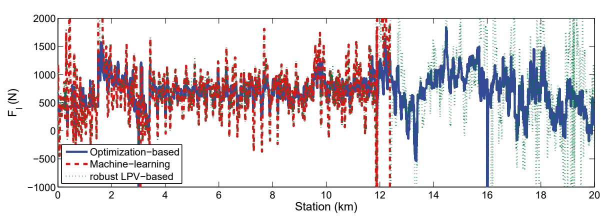
The proposed robust LPV-based control strategy is able preserve the benefits of the machine-learning-based agent



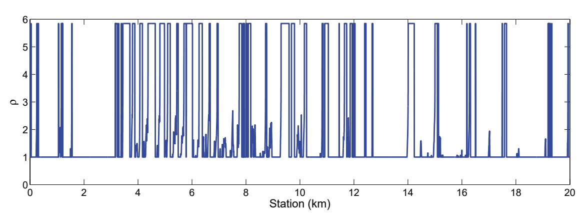
(a) Terrain characteristics



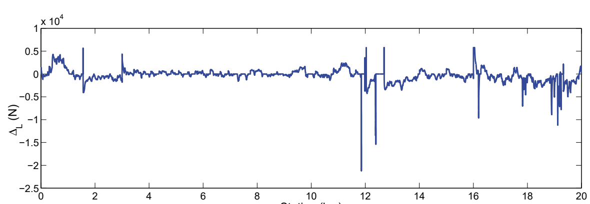
(b) Velocity profiles of the vehicle



(c) Longitudinal control force intervention



(d) Scheduling variable ρ_L



(e) Known disturbance Δ_L

Fig. 3. Simulation scenario on the freeway section of A36

in the eco-cruise control. The resulted LPV-based eco-cruise control requires low quantity of on-line optimization, which facilitates the implementation of the method. The expensive computation processes, such as the learning and the iterative control design are performed off-line. Simultaneously, the minimum performance level of the controlled system is successfully guaranteed, even at the degradation of the machine-learning-based agent of it.

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