Online Estimation of a Mechanical Driveline Parameters of a Hybrid Bus

Nevaranta Niko, Montonen Henri, Lindh Tuomo

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N. Nevaranta, J-H. Montonen, and T. Lindh
LAPPEENRANTA UNIVERSITY OF TECHNOLOGY
Department of Electrical Engineering
P.O.Box 20, 53851 Lappeenranta
Lappeenranta, Finland
Email: niko.nevaranta@lut.fi
URL: https://www.lut.fi/web/en/

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Abstract

This paper addresses issues in real-time identification of mechanical driveline parameters of a hybrid-electric bus. The mechanical system is excited by an artificially generated excitation signal, namely a pseudo-random binary signal (PRBS), and the parameters are identified using a recursive output error algorithm with filtered observations (OEFO). The identification routine is experimentally validated by using a hybridized bus as a test vehicle and considering on-road measurements with a moderate velocity in series electric operation mode.

Introduction

The mechanical driveline system in a modern hybrid mobile equipment, such as hybrid vehicles or heavy working machines, is typically composed of combustion engine, shafts, wheels, motor/generator, transmission systems, and clutch, to name but a few. Since these components are mechanically coupled together, resonances are inherently formed due to presence of flexibilities. Depending on the driveline design, the most crucial first eigenfrequencies, in other words, the dominant mechanical resonances typically lies in the range of 5 Hz to 50 Hz at low frequencies [1]. The low frequency oscillations related to the dominant resonant mode can be typically passively damped via the driveline components. However, in some mobile equipment, the resonances can results in an adverse driveline oscillations or mechanical stresses, if the vehicle is subjected to disturbances [2].

The estimation and monitoring of a mechanical system in electric drives has become an increasingly important feature in various industrial applications such as robotics [3], machine tools [4], industrial drivetrains [5], just to name but a few typical examples. Artificial test signals, such as a pseudo-random binary signal (PRBS) or multi-sine, are commonly applied when the natural input to the system does not offer enough excitation to the system for identification. Typical example of using broadband excitation signals in electrically powered vehicle applications is the ones generated by the battery management system (BMS) for the identification of the energy storage system dynamics [6],[7]. Because electric drives are important element of drivelines of the hybrid vehicles, these can be similarly used to provide additional excitation by generating excitation signal that is superposed to the torque reference of the motor control, as has been experimentally shown in [1], [2]. Despite the fact that parameter estimation of mechanical systems in electric drives is well-established research field, to the authors knowledge, there are only a few studies that focus on the issues related to the use of system identification approaches to the estimation of mechanical driveline parameters in hybrid or electric vehicles. In [1] a commissioning routines for hybrid city bus has been discussed and experimental identification is used to the estimate parametric models of the driveline. In [8], [9] a non-parametric offline identification of a nonlinear drivelines of electric vehicles (EVs) has been studied by exciting the mechanical driveline with (PRBS) test signals. For the purpose of controller design, these identification problems has considered linear system identification method in order to have simplified model of the drivetrain. Another offline identification approach has been introduced in [10], where prediction error method (PEM) is considered for estimation of mechanical parameters of a truck driveline. Another paper [11] proposes modal analysis based algorithm that can be used to analyze different drivelines and for control design. In a simulation study [12], a PRBS excitation signal has been used to identify the driveline dynamics to estimate an autoregressive with exogenous input model (ARX) for model predictive control (MPC). Another study [13] considers recursive least squares (RLS) algorithm to obtain model of the flexible driveshaft in an engine-in-a-loop simulation environment.

Based on the literature review, there are not many studies that have discussed or considered real-time approaches for the estimation of mechanical parameters during on-road operation. In [14] an extended Kalman filter (EKF) is applied for real-time monitoring of driveline dynamics, but the paper does not discuss the parameter estimation in detail. In [15] the online recursive identification of elastic driveline is studied by simulations. Some studies, such as [16], have considered bootstrap algorithm for time varying parameter estimation of driveline model to be used with adaptive linear quadratic (LQ) controller. As the signal analysis based diagnostics and monitoring of electric drivetrain components have become important topic in modern HEVs [17], it is also important to consider the identification of mechanical system as well in order to obtain information about the possible changes. In this paper, the issues related to the real-time identification of a mechanical driveline parameters of a hybrid-electric bus is addressed. The mechanical system is excited using a pseudo-random binary signal (PRBS) and the parameters are identified by using a recursive output error algorithm with filtered observations (OEFO). The parameter estimation approach is experimentally verified with a hybridized city bus vehicle by considering on-road tests in the series electric mode.

Driveline of a Hybrid Bus

In this paper, the identification experiments are carried out and evaluated on an actual hybrid bus vehicle that was designed and constructed at Lappeenranta University of Technology (LUT). The components of the driveline can be found in Fig. 1, where a 2.5-L combustion engine is connected to a 55-kW outer rotor permanent magnet (PM) generator and the traction motor is a 6-phase PM that is connected with a Cardan shaft running the rear differential and drive shafts.

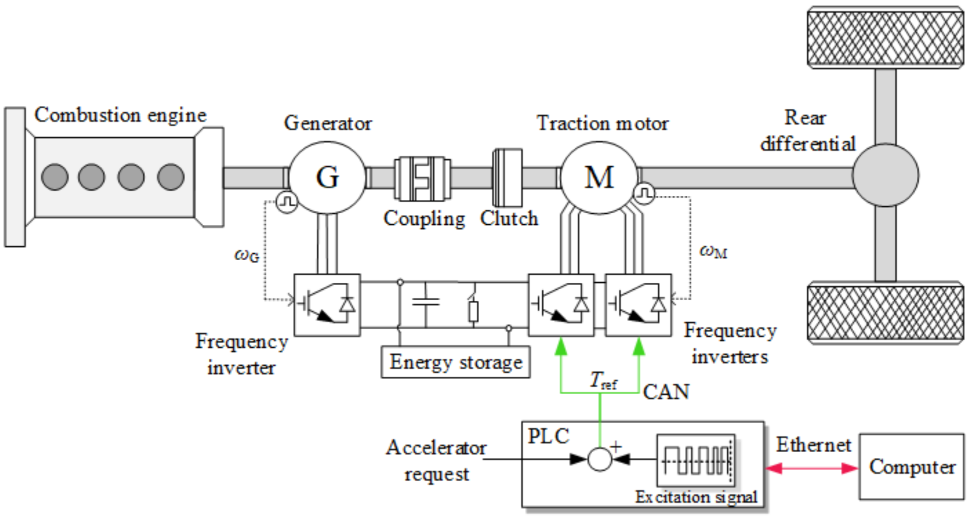

Fig. 1: Components of the driveline: a combustion engine, a permanent magnet (PM) generator, coupling, a clutch, energy storage, frequency inverters and a PM traction motor. The control and artificial excitation signals are generated with a programmable logic controller (PLC).

The operation modes of the hybrid bus are divided to series or parallel modes. In the series hybrid or electric vehicle mode, i.e. at low velocities, the coupling between the traction motor and generator is opened. Thus, the traction motor relays the torque to the wheels. When the velocity of the bus exceed, the clutch is closed and the bus operates in a hybrid parallel hybrid mode. It is emphasized that in this paper, the online identification of the mechanical driveline is studied in the series electric vehicle mode, thus the coupling between the generator and traction motor is open during the tests.

Identification Experiments

In the experimental identification, the PRBS is generated by a ten-cell shift register and superposed to the torque reference of the frequency inverters of the traction motor as is illustrated in Fig. 1. As is also depicted in Fig. 1, the velocity of the PM traction motor ω_M is measured with a resolver connected to its shaft that is considered as the output signal in the identification process, hence $y(k) = \omega_M$. The torque signals T_{M1} and T_{M2} of the both inverter controlling the traction motor are collected during the identification experiments. These torque signals are used to determine the total torque T_{tot}, that is considered as an input signal, thus $u(k) = T_{tot} = T_{M1} + T_{M2}$. As an illustrative example, in Fig. 2 the measured velocity and torque from three on-road identification experiments are with a near constant velocity.

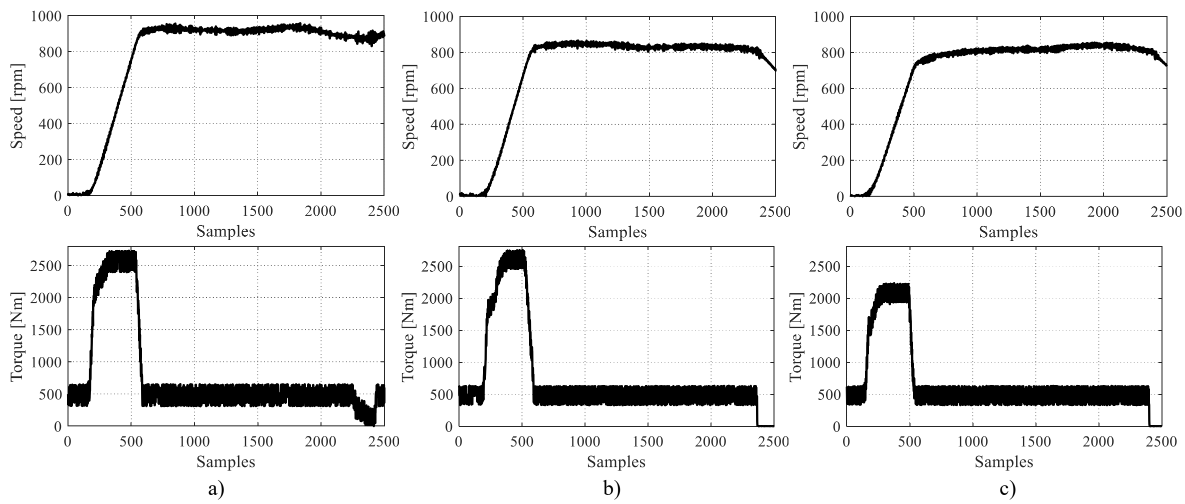

Fig. 2: The collected torque T_{tot} and velocity ω_M signals during the identification experiments. The sample time for data acquisition is set to 10 ms.

In this paper, the measured results from several identification tests similar as shown in Fig. 2 are used to evaluate the applicability of recursive OEFO techniques for the real-time estimation of mechanical driveline parameters. Note that, the driving profiles depicted in Fig. 2 are given as an illustrative example in order to show torque and velocity signals during identification routine. In other words, for the identification process several different data sets are used and there are variation between the tests due to driver interaction, road and weather conditions. More discussion about the identification experiments can be found in [1].

Online Identification Algorithm

By considering *a priori* adjustable predictor with following form

$$\hat{y}(k) = \theta^T(k)\phi(k), \tag{1}$$

where the estimated parameter vector $\theta(k)$ and the regression vector $\phi(k)$ are defined as

$$\theta^T(k) = [\hat{a}_1(k), ..., \hat{a}_{n_A}(k), \hat{b}_1(k), ..., \hat{b}_{n_B}(k)], \tag{2}$$

$$\phi^T(k) = [-y(k), ..., -y(k-n_A+1), u(k-d), ..., u(k-d-n_B+1)], \tag{3}$$

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where the $\hat{a}_1(k),..,\hat{a}_{n_A}(k)$ and $\hat{b}_1(k),...,\hat{b}_{n_B}(k)$ denotes the denominator $A(z)$ and numerator $B(z)$ parameter of the system model to be estimated with the orders n_A and n_B. The d is the time delay. The basic form for the recursive parameter estimation algorithm can be expressed as

$$\theta^{\mathrm{T}}(k+1) = \theta^{\mathrm{T}}(k) + \mathbf{F}(k)\Phi(k)\varepsilon(k+1), \tag{4}$$

$$\mathbf{F}(k+1)^{-1} = \lambda_1(k)\mathbf{F}(k)^{-1} + \lambda_2(k)\Phi(k)\Phi(k)^{\mathrm{T}}, \tag{5}$$

$$\varepsilon(k+1) = \frac{\varepsilon^0(k+1)}{1+\Phi(k)^{\mathrm{T}}\mathbf{F}(k)\Phi(k)}, \tag{6}$$

where $\varepsilon(k)$ is the postepriori prediction error, $\varepsilon^0(k)$ is the priori prediction error, $\mathbf{F}(k)$ denotes a covariance matrix, and $\lambda_1(k)$ and $\lambda_2(k)$ are the gains for the forgetting factor control to get various profiles for the adaption. The observation vector $\Phi(k)$ for OEFO algorithm is formed by filtering the regression vector

$$\Phi(k) = \frac{1}{L(z)}\phi(k), \tag{7}$$

where $L(z) = \hat{A}(z)$ is an estimation of the polynomial $A(z)$ obtained by another estimation algorithm. In this paper, an output error (OE) model has been estimated in advance and used as a filter for the OEFO algorithm. This algorithm is implemented to the PLC and initialized so that the model structure selection for system model parameters is reasonable. Naturally, the system dynamics is varying as on-road measurements are considered. Thus, it is reasonable to consider forgetting factor updating routine [19] in the algorithm. Here, a decreasing gain combined with a constant trace is considered to control the adaption gain with following tuning values $tr\mathbf{F}(0)$ = 0.01 and λ_1 = 0.993.

Experimental Results

The experimental tests are carried out with an actual hybrid bus shown in Fig. 3. More details about the vehicle under study can be found in [1] and [18].

Fig. 3: Hybridized bus as a test environment.

Due to the fact that during the on-road experiments the mechanical system is loaded by unknown external forces, it is expected that the parameters related to the system dynamics are time varying in nature. For this reason, at first, the applicability of the OEFO algorithm for the parameter estimation is evaluated by estimating several local models from the on-road experiments. These models are used to show that the chosen model structure can capture the essential system dynamics, and more importantly, the frequency band around the first resonance frequency of the system. In Fig. 4 the obtained online parametric models are compared with the corresponding offline post-processed spectral transfer function estimates. All models estimated with the OEFO have been obtained similarly, in other words, by considering polynomial model structure with orders $n_A = 4$ and $n_B = 4$ with delay $d = 1$, and the number of samples N in the estimation is 1024. It is well known that a resonating system with one dominating frequency can be approximated by a third order system. Here, by testing different model order combinations the fourth

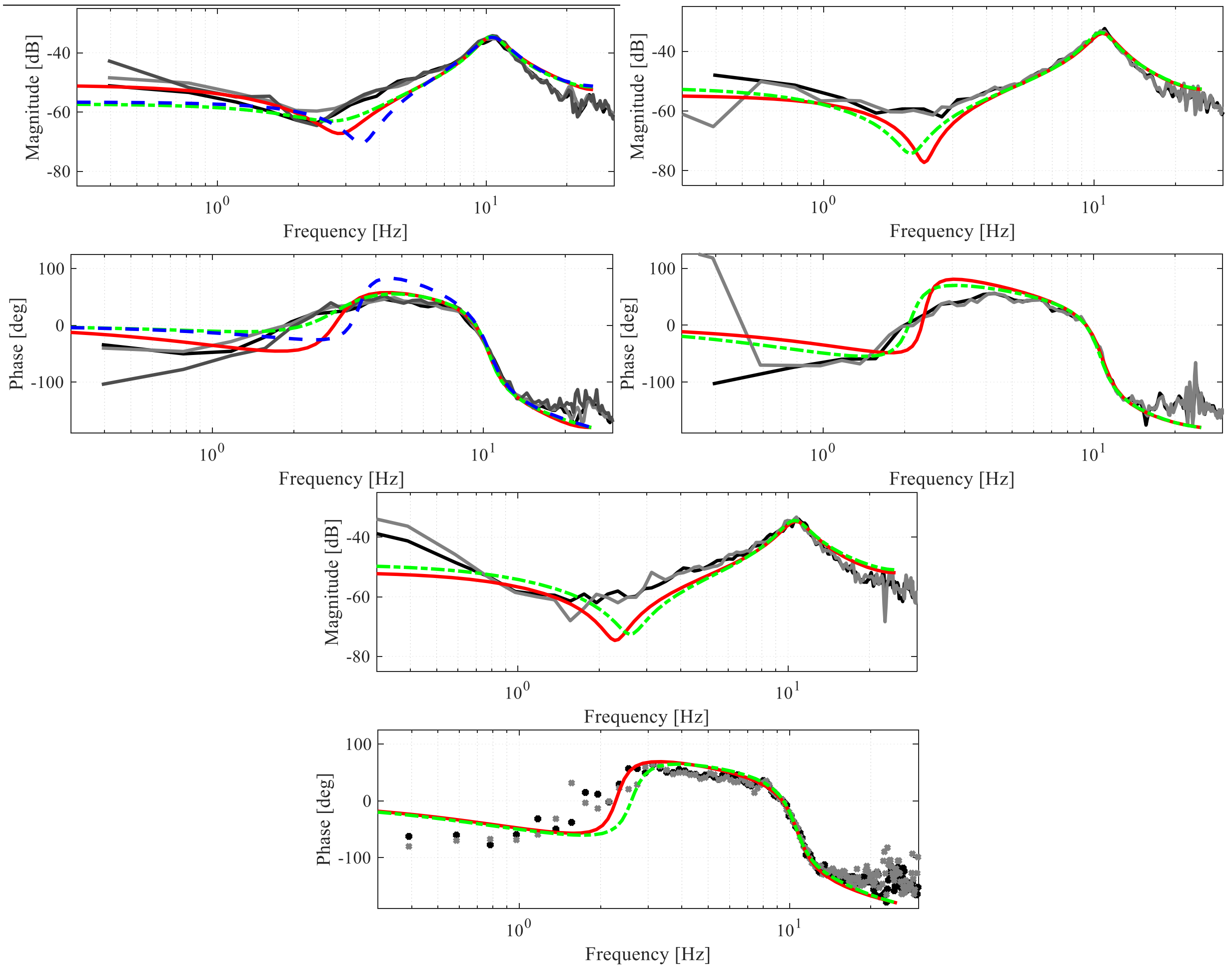

Fig. 4: Frequency responses of the online estimated local models from the on-road experiments compared to the post-post processed frequency responses calculated from the same data. The models has been estimated using a sample time $T_s = 0.02$ seconds.

order model has been selected which is close to the third order approximation. The unknown parameter vector θ is initialized to zero, and for this reason, a large initial value for the covariance matrix is required, thus in this paper $\mathbf{F}(0) = 1000 \cdot \mathbf{I}$ ($\mathbf{I}$ is an identity matrix) is chosen. Although small discrepancies can be noticed, the results in Fig. 4 clearly indicate that the local online estimated models are in a satisfactory agreement with the offline post-processed frequency responses. Note that, in principle the offline and online estimated results are not comparable because of the fundamental differences in the estimation routine, but the offline estimated frequency responses can be used to argue whether the chosen model structure can consistently reproduce parameter values in different operation points. Evidently, the online estimation captures the system dynamics as the resonance is clearly noticeable from the obtained models.

Model Validation

Model validation is an important step of the system identification process. However, when system with changing parameters is considered the validation process can be problematic, because of lack of suitable and independent validation data. Nevertheless, based on the identified frequency responses shown in Fig. 4, the online identification routine produces reasonable estimates. To further validate this observation, the a pole-zero distribution of the identified output-error (OE) models are shown in Fig. 5. Note, that a corresponding third order dynamics are shown. The given result clearly shows that the dominant poles are consistent between the experiments indicating that the resonance region is captured accurately by the estimation. There is also a noticeable uncertainty in the estimated low frequency dynamics that is

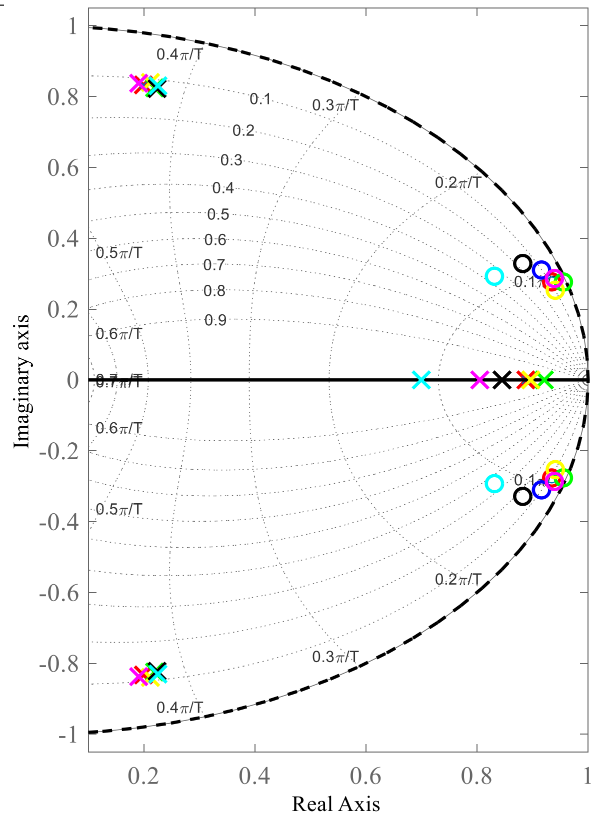

Fig. 5: Pole-zero distribution of the identified models from different identification experiments. There are 8 identified models presented with different colors.

due to variations in the experimental tests.

Conclusion

Electrically powered vehicles with high calculation capacity power electronics and control devices gives the possibility to implement system identification techniques and generate artificial excitation signals, to be used as part of the control system. Even though, the road excitations and the changes in the driving profile already provide good identifiability condition, the identification experiment can be supported by considering a known artificial excitation signal. In this paper, the real-time identification of the mechanical driveline parameters of hybrid bus was investigated when the vehicle is operated in series electric mode. A pseudo-random binary signal (PRBS) was generated with a PLC that provided the reference signals for the frequency inverters connected to the traction motor. Based on the measured input-output data, the studied OEFO estimation approach with an appropriate model structure selection was applied for the parameter estimation process.

The results showed that the driveline resonance can be monitored by using a recursive identification algorithm. In this paper, the hybrid bus vehicle was operated with a nearly constant velocity under varying operation conditions and the parameter estimation was used to obtain local models for the driveline. The presented results show that a reasonable model approximation can be obtained by a recursive parameter estimation approach. The obtained results were consistent with each other especially in the resonance frequency region, indicating the possibility to use the estimation approach, for instance, as a part of active oscillation damping method.

References

[1] Montonen J-H., Nevaranta, N., Lindh T., Alho J., Immonen P., and Pyrhönen O.: Experimental Identification and Parameter Estimation of the Mechanical Driveline of a Hybrid Bus, IEEE Trans. Ind. Electron., vol. 65, no. 7, pp. 5921–5930, July 2018.

[2] Amann N., Böcker J., and Schulz B.: Active damping of drive train oscillations for an electrically driven vehicle, IEEE/ASME Trans. Mechatronics., vol. 9, no. 4, pp. 697–700, Dec. 2004.

[3] Östring M., Gunnarsson S., and Norrlf M.: Closed-loop identification of an industrial robot containing flexibilities, Control Eng. Pract., vol. 1, no. 11, pp. 291–300, 2003.

[4] Peretti L., and Zigliotto M.: Identification of mechanical load for electrical drives commissioning Labelling machine case study, in Proc. EUROCON, pp. 797–803, May 2009.

[5] Wahrburg A., Jelavic E., Klose S., and Listmann K. D.: Robust semi-automatic identification of compliantly coupled two-mass-systems, IFAC-PapersOnLine, vol. 50, no. 1, pp. 14569–14574, July 2017.

[6] Al Nazer, R., Cattin V., Granjon P., Montaru M., and Ranieri, M.: Broadband identification of battery electrical impedance for HEVs, IEEE Trans. on Vehicular Technology, vol. 62, no. 7, pp. 2896–2905, May 2013.

[7] Relan R., Firouz, Y., Timmermans J-M., and Schoukens, J.: Data-driven nonlinear identification of Li-ion battery based on a frequency domain nonparametric analysis, IEEE Trans. on Control Systems Technology, vol. 25, no. 5 Sep. 2017.

[8] Berriri M., Chevrel P., and Lefebvre D.: Vehicle driveability improvement by prediction and compensation of the shaft torque: a state-space approach, in Proc. of 2007 European Contr. Conf. (ECC), Kos, Greece, 2007, pp. 78–84.

[9] Böcker J., Amann N., and Schulz B.: Active suppression of torsional oscillations, in Proc. 3rd IFAC Symp. on Mechatronic Syst., Sydney, Australia, Sep. 2004, pp. 325–330.

[10] Templin P.: Simultaneous estimation of driveline dynamics and backlash size for control design, in Proc. 17th Int. Conf. on Contr. Appl., San Antonio, Texas, USA, Sep. 2008, pp. 13–18.

[11] Fleischer M.: Reduced model identification for traction drive-trains, in Proc. of 40th IAS Annual Meeting, vol. 4, no. 2, pp. 2873–2879, Oct. 2005.

[12] Caruntu, C.: Real-time simulation of a network-controlled vehicle drivetrain based on model predictive control, Bul. Inst. Polit. Iasi., pp. 43–58, 2013.

[13] Kang M., and Shen T.: Modeling and control for engine-in-loop simulation system, Jour. of System Design ans Dynamics, vol. 7, no. 4, pp. 428440 , 2013.

[14] Grotjahn M., Quernheim L., and Zemke S.: Modelling and identification of car driveline dynamics for anti-jerk controller design, IEEE Int. Conf. on Mechatronics, July 2006, pp.131–136.

[15] Dai, P., Huang, Y., Hao, D., and Zhang, T.: On-line model recursive identification for variable parameters of driveline vibration, Int. Powertrains, Fuels and Lubricants Meeting, Beijing, China, Oct. 2017, pp.1–12.

[16] Webersinke L., Augenstein L., Kiencke U., and Hertweck, M.: Adaptive Linear Quadratic Control for High Dynamical and Comfortable Behavior of a Heavy Truck, SAE Int. J. Commer. Veh., vol. 1, 2009, pp. 17–24.

[17] Rajagopalan S., Habetler T. G., Kral C., and Pirker F.: Monitoring and Diagnostics for Electric Drivetrain Components in HEVs, in Proc. 2006 SAE World Congress, Detroit, April 2006, pp. 1–11.

[18] Lindh P., Tehrani G. M, Lindh T., Montonen J-H, Pyrhönen J., Sopanen J. T., Niemelä M., Alexandrova Y., Immonen P., Aarniovuori L and Polikarpova M.: Multidisciplinary Design of a Permanent-Magnet Traction Motor for a Hybrid Bus Taking the Load Cycle into Account, IEEE Trans. Ind. Electron., vol. 63, no. 6, pp. 3397–3408, June 2016.

[19] Landau I. D. and Zito G.: Digital Control Systems: Design, Identification and Implementation, 1st ed. Berlin, Germany: Springer-Verlag, 2006.