Unknown load torque estimation on rotary drivetrains with exploitation of angular periodicity in an extended Kalman filter

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Abstract
Accurate knowledge of the torsional vibrations is key for condition monitoring, control and design optimization of mechatronic drivetrains. An often applied solution is to combine the knowledge of the system dynamics in the form of a physics-based model with an informative but limited set of measurements in a stochastic estimation algorithm. A critical difficulty in this estimation arises from the external torques acting on the drivetrain. For many rotary drivetrains, these external torques show cyclic behavior in function of the rotational position to some extent. This contribution presents a strategy to exploit such behavior in an augmented extended Kalman filter. The strategy is experimentally validated on a mechatronic drivetrain setup, consisting of a back-to-back induction motor with a cardan axle connection. The root-mean-square error of the estimated load torque with regard to a validation torque sensor is used to compare the results with a conventional estimator. A significant reduction in root-mean-square error is obtained for the new strategy as compared to the conventional augmented Kalman filter for a number of validation experiments. The amount of error reduction is shown to be dependent on the relative contribution of the cyclic term to the overall unknown torque.

1 Introduction

In mechatronic drivetrains, accurate knowledge of the torsional vibrations is key for condition monitoring, predictive maintenance, control and design optimization. While physics-based models provide predictions for these vibrations, obtaining accurate predictions is very challenging due to the complexity of the occurring physical phenomena. Alternatively, direct torque measurement can be employed, with the drawback that it is often intrusive and expensive. In most industrial cases, the available sensors only provide indirect measurements of the torque such as position, speed, and acceleration. Consequently, an often applied solution is to combine such indirect measurements with a physics-based model in a stochastic estimation method, for example a Kalman filter. The estimation accounts for the model inaccuracies by incorporating a model uncertainty. The classical Kalman filter provides estimates of the states, while the extension towards coupled state/input/parameter estimation is obtained by augmenting the state vector with the inputs and the parameters of interest ([2],[3]). Forrier [1] developed one of the first virtual load sensors by applying an augmented Kalman filter on the mechatronic drivetrain setup depicted in Figure 1, combining a lumped-parameter model of the system with a set of indirect sensor measurements. Concurrent estimation of the states and the unknown load motor torque is achieved by augmenting the states with the unknown torque and using a random walk model for the augmented model equation. The approach was experimentally validated by comparing the estimated torque to the measurement of an HBM T40B torque sensor. Including rotational acceleration measurements yielded accurate and broadband load torque estimation, whereas using rotational speed sensors resulted in reduced accuracy and bandwidth.

The described approach uses a random walk model for the unknown load torque, allowing to track fast and high amplitude variations only by assuming a high variance value on the related noise model, such that the model is significantly corrected by the measurements. In [4], such random walk model is enhanced by adapting the variance value of the noise model based on the cyclic dependency of the unknown torque in function of the rotational position, as commonly observed in rotary drivetrain applications. The aim of this contribution is to go one step further and improve also the model prediction itself.

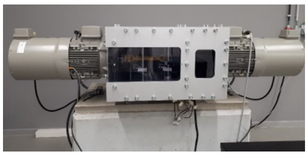


Figure 1: Back-to-back induction motor drivetrain setup.

2 Estimation method

The details of the model and the previously developed estimation can be found in [1], but the main aspects are summarized here. The setup consists of two back-to-back induction motors with cardan shaft connection. The electric motor on the drive side is modelled with a lumped-parameter model, while the load motor is considered as an external torque input in the model. The system model is obtained by coupling the electric motor model with a lumped-parameter model for the mechanical transmission. The four electric motor model states are two equivalent stator currents and two equivalent rotor magnetic fluxes, while the four mechanical states are rotational position and speed at motor and load side. By augmenting the states with the unknown load torque, this results in a total of nine states. The known inputs to this model are the two stator voltages. Two measurement sets are considered, referred to as full sensor set and reduced sensor set. The full sensor set consists of the drive motor rotational position, two equivalent stator currents, and rotational accelerations at drive and load side. The reduced set is the same, except that the rotational accelerations are replaced by rotational speed measurements.

The used estimator is an augmented extended Kalman filter. Instead of estimating the total load torque with a random walk model such as previously done in [1], the cyclic relation towards the rotational position is taken into account to obtain an improved model with a reduced variance value for the related model noise.

The unknown torque of the load motor T can be described as follows:

$$T = T_{cyclic}(\theta_L) + T_{dev} \tag{1}$$

where $T_{cyclic}(\theta_L)$ denotes a cyclic term which depends only on the rotational position of the load motor θ_L, and T_{dev} is the deviation with regard to this cyclic relation. The method can be summarized as follows:

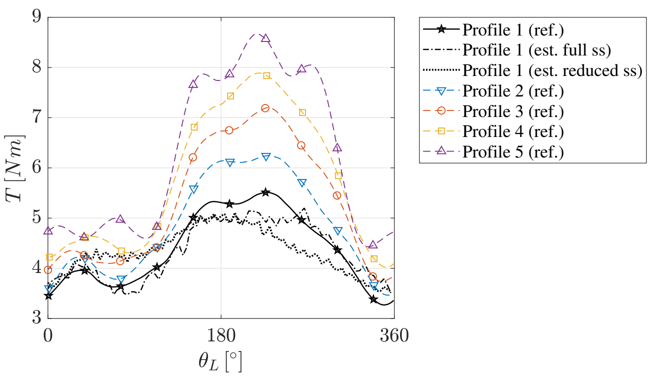
1. The cyclic relation is parameterized as $T_{cyclic}(\theta_L, \mathbf{p})$ where $\mathbf{p}$ denotes the parameter vector. The parameters are estimated prior to the state-input estimation, using the method described in [5].

2. The cyclic parameter relation is used to generate a deterministic cyclic input in the model equations. The deviation of the unknown load torque with regard to this cyclic relation is now estimated as an augmented state. A random walk model is assumed for this deviation term, but with a reduced variance value for the model noise compared to the similar model for the total torque. A reduction factor of 0.1 is adopted here.

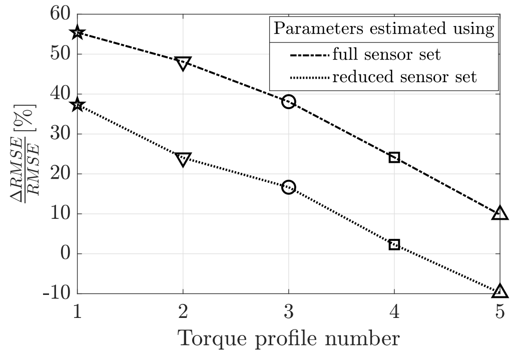
3 Results

The estimation method is experimentally validated by quantifying the root-mean-square error (RMSE) of the estimated load torque with relation to the measurement of an HBM T40B torque sensor, and by comparing the RMSE results with those of the previously developed estimator. Five load torque profiles are considered for the validation, as illustrated in Figure 2a. Note that the drawn profiles are only valid for a single rotation, but the variation between different rotations is much smaller compared to the differences between the five profiles. The validation experiments are now described. First, the cyclic parameter relation is estimated for a data set with load torque profile 1, once using the full sensor set and once using the reduced sensor set. Second, the estimated parameter vectors for torque profile 1 describe a cyclic input for the load torque in the model equations while the remaining term is estimated using a reduced sensor set for all five profiles. The relative improvements compared to the original estimation in terms of RMSE are plotted in Figure 2b.

It can be seen on Figure 2a that the estimated cyclic parameter relation for profile 1 is closer to the reference profile for the full sensor set compared to the reduced set. This results in more significant RMSE improvements when using the estimated parameters with the full sensor set, as depicted in Figure 2b. The results for profile



(a) Load torque profiles for validation.



(b) Relative RMSE improvement compared to conventional estimation.

Figure 2: Results.

1 show the strongest RMSE improvements, which is expected since the parameters of the cyclic term are estimated based on the profile 1 data, making the relative contribution of the cyclic term to the overall load torque the highest. With increasing profile number, the relative contribution of the cyclic term (based on profile 1) to the overall load torque decreases, leading to a decrease in RMSE improvement. For profile 5 with the parameters estimated using the reduced set, the obtained RMSE is worse compared to conventional estimation.

4 Conclusion

This contribution proposed a method that utilizes cyclic behaviour of an unknown input in an augmented extended Kalman filter. The method is validated on a mechatronic drivetrain setup for load torque estimation. Compared to using a conventional augmented Kalman filter, the new strategy achieves a significant reduction in root-mean-square error for multiple validation experiments, with the amount of error reduction depending on the relative contribution of the cyclic term to the overall unknown input. These findings confirm the notion that incorporating additional information about the input behavior improves the estimation quality. However, if the added information deviates too far from reality, it creates an adverse effect.

Acknowledgements

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