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Industrial Applications of the Kalman Filter: A Review

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***Abstract*—The Kalman filter has received a huge interest from the industrial electronics community and has played a key role in many engineering fields since the 70s, ranging, without being exhaustive, trajectory estimation, state and parameter estimation for control or diagnosis, data merging, signal processing and so on. This paper provides a brief overview of the industrial applications and implementation issues of the Kalman filter in six topics of the industrial electronics community, highlighting some relevant reference papers and giving future research trends.**

***Index Terms*—Kalman filter, state estimation, implementation issues, industrial applications.**

I. Introduction

MANY industrial applications require to measure a large number of physical variables so as to own a sufficient quantity and quality of information on the system state and to ensure the required level of performance. However, the measurement of some physical quantities may not be possible or desired, mainly because of the cost reduction and/or the increase in system reliability. In this context, the Kalman filter (KF), whose 50th anniversary occured in 2010, has played a key role in many industrial applications of the engineering professions since the 70s, including without being exhaustive, trajectory estimation, state prediction for control or diagnosis, data merging, and so on.

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Many researches have been dedicated to the implementation and performance improvement of the KF, namely the numerical stability improvement, the computation time reduction or the study of effective implementations. The main objective of this paper, designed as a concluding paper to the Special Section of these Transactions on the industrial applications and implementation issues of the Kalman filter [1], is to highlight the latest theoretical and experimental advances and to emphasize practical implementation issues of this state estimator.

The scope of this paper is dedicated to the KF applications in five topics covered by the industrial electronics society, namely i) sensorless control, diagnosis and fault-tolerant control of AC drives, ii) distributed generation and storage systems, iii) robotics, vision and sensor fusion techniques, iv) applications in signal processing and instrumentation and v) real-time implementation of a KF for industrial control systems. Therefore, this paper is organized in seven sections: section II gives a brief overview of Kalman filtering theory, and sections III to VI are dedicated to the items cited above. Finally, conclusions and future trends are discussed in the last section.

II. A brief overview of Kalman filtering theory

In his famous and now 50-year-old publication [2], Rudolf Emil Kalman proposed an optimal recursive estimator of the state of an uncertain dynamic system. Although it is based on advanced results of probability theory, its final formulation is remarkably simple and effective to implement on a digital target. The first derivation was made for a discrete-time finite-dimensional linear stochastic process

$$X_{[k+1]} = A\,X_{[k]} + B\,U_{[k]} + G\,V_{[k]} \quad (1)$$
$$Y_{[k+1]} = C\,X_{[k+1]} + W_{[k+1]} \quad (2)$$

where $X \in I\!R^n$ is the state vector, $U \in I\!R^l$ is a deterministic process input and $y \in I\!R^m$ is the measurement. The two random variables V and W respectively represent the process and the measurement noises: V bears the model uncertainty, whereas W bears the sensor uncertainty and digital quantization effects. These noises are assumed to be zero mean, white and independent of each other, with respective covariance matrices Q anr R. All the matrices A, B, G and C are deterministic and may also depend on time. Since the measurement y does not exhaustively inform us on the current situation of the process, the Kalman filter aims at providing an estimate of the process state X. This filter is made of two groups of equations:

- *the time update equations*, which try to predict the state value at time $k{+}1$ based on the transition equation (Eq. 1) and on the set of all the measurements until time k, $\mathcal{Y}_{[k]} = \{Y_{[0]}, Y_{[1]}, \ldots Y_{[k]}\}$. This prediction is deduced from a previously derived estimation of the state at time k, $X_{e[k]}$:

$$\begin{aligned} X_{p[k+1]} &= I\!\!E\left[X_{[k+1]} \mid \mathcal{Y}_{[k]}\right] && (3)\\ &= A\,X_{e[k]} + B\,U_{[k]} && (4)\\ P_{p[k+1]} &= I\!\!E\left[\widetilde{X}_{p[k+1]}\,\widetilde{X}_{p[k+1]}{}^{t} \mid \mathcal{Y}_{[k]}\right] && (5)\\ &= A\,P_{e[k]}\,A^{t} + Q && (6)\\ \text{with } \widetilde{X}_{p[k+1]} &= X_{[k+1]} - X_{p[k+1]} && (7) \end{aligned}$$

  In Eq. 5 and 6, $P_{e[k]}$ and $P_{p[k+1]}$ are respectively the estimation error covariance matrix at time k and the prediction error covariance matrix at time $k+1$. Both provide a quantitative evaluation of the quality of this estimation and of this prediction.

- *the measurement update equations*, which try to improve the prediction $X_{p[k+1]}$ thanks to the measurement available at time $k+1$:

$$\begin{aligned} X_{e[k+1]} &= X_{p[k+1]} + K_{[k+1]}\,\widetilde{Y}_{p[k+1]} && (8)\\ \text{with } \widetilde{Y}_{p[k+1]} &= Y_{[k+1]} - C\,X_{p[k+1]} && (9) \end{aligned}$$

  This correction of the prediction will be optimal if the estimation error is statistically orthogonal [3] to the measurement prediction error $\widetilde{Y}_{p[k+1]}$, which is sometimes called the measurement innovation. This way, all the information that the current measurement $Y_{[k+1]}$ has about the current value of the state and that is not conveyed by the set of the previous measurements $\mathcal{Y}_{[k]}$ will be used to derive an estimate of $X_{[k+1]}$:

$$I\!\!E\left[\widetilde{X}_{e[k+1]}\,\widetilde{Y}_{p[k+1]}{}^{t}\right] = 0 \Longrightarrow$$

$$K_{[k+1]} = P_{p[k+1]}\,C^{t}\left(C\,P_{p[k+1]}\,C^{t} + R\right)^{-1} \quad (10)$$

  The covariance matrix of the estimation error can then be computed as

$$P_{e[k+1]} = P_{p[k+1]} - K_{[k+1]}\,C\,P_{p[k+1]} \quad (11)$$

These equations are repeated at each time sample, the previous state estimate being first used to compute a state prediction (Eq. 4 and 6), then a new state estimation (Eq. 8, 10 and 11).

In some publications, $X_{p[k+1]}$ and $X_{e[k+1]}$ are written as $X_{[k+1|k]}$ and $X_{[k+1|k+1]}$, but this notation increases the length of the equations and may frighten some students. As they can be considered as the *a priori* and the *a posteriori* state estimates, since they can respectively be computed before and after the availability of the measurement $Y_{[k+1]}$, they may also be written as $X^{-}{}_{[k+1]}$ and $X^{+}{}_{[k+1]}$. Unfortunately, the notation of vectors and matrices is a major concern for the understanding of discrete-time Kalman filtering.

This first derivation of the Kalman filter has been extended to linear continuous-time finite-dimensional stochastic processes: if the state equations can be written as

$$\begin{aligned} \dot{X}(t) &= A\,X(t) + B\,U(t) + G\,V(t) && (12)\\ Y(t) &= C\,X(t) + W(t) && (13) \end{aligned}$$

then an optimal state estimate $\hat{X}$ can be obtained by a Kalman-Bucy filter [4] defined as

$$\begin{aligned} &\dot{\hat{X}}(t) = A\,\hat{X}(t) + B\,U(t) + K(t)\,\left(y(t) - C\,\hat{X}(t)\right) && (14)\\ &K(t) = P(t)\,C^{t}\,R^{-1} && (15)\\ &\dot{P}(t) = A\,P(t) + P(t)\,A^{t} + Q - P(t)\,C^{t}\,R^{-1}\,C\,P(t) && (16) \end{aligned}$$

Finally, the original Kalman filter has also been extended to a discrete-time non-linear stochastic process. In such a framework, the optimal Kalman filter [5] can often not be computed, and approximations, such as the well known extended Kalman filter, must be used. The set of all of these filters allow engineers and researchers to solve many problems in a wide range of applications.

To illustrate this overview with a simple example, we may consider the case of a target moving in a one-dimensional space whose position $x(t)$ is observed with both an acceleration sensor and a position sensor. This motion observer is called a disturbance observer in robotics [6] and an angle tracking observer in electrical engineering [7]. From Taylor approximations, one may modelize the target motion as a linear stochastic process:

$$\begin{aligned} X_{[k+1]} &= A\,X_{[k]} + G\,v_{[k]} && (17)\\ Y_{[k+1]} &= C\,X_{[k+1]} + W_{[k+1]} && (18)\\ \text{with } A &= \begin{pmatrix}1&1&1\\0&1&2\\0&0&1\end{pmatrix}, G^{t} = \begin{pmatrix}1\\3\\3\end{pmatrix}, C^{t} = \begin{pmatrix}1&0\\0&0\\0&1\end{pmatrix}, && (19) \end{aligned}$$

where the three components of the state are defined as $x(kT_s)$, $\frac{dx}{dt}(kT_s)\,T_s$, $\frac{d^2x}{dt^2}(kT_s)\,T_s^2/2$, T_s being the sampling period and where $v[k] = \frac{d^3x}{dt^3}(kT_s)\,T_s^3/6$ is derived from the third-order derivative of the position, sometimes called the jerk, and considered as a scalar zero-mean random variable of variance Q. Since this process is observable, a Kalman filter can be designed from this model using Eqs. 4, 6, 8, 9, 10 and 11. For constant values of Q and R, the Kalman correction gain

K goes to a constant which does not depend on the initial value of the covariance matrices and can be computed offline, reducing the computational cost of this Kalman filter to a few elementary arithmetic operations. Since the measurement noises can reasonably be regarded as uncorrelated, the R matrix is diagonal and can be written as $R = \mathrm{diag}\left(\sigma_p^2, \sigma_a^2\right)$. Finally, since the Kalman correction gain is left unchanged when Q, R and $P_e(0)$ are all multiplied by the same scalar [8], this means that the final value of K only depends on σ_p^2/Q and σ_a^2/Q.

Other academical examples, more detailed explanations and implementation issues may be found in [9]–[11]. Historical issues may also be found in [12], [13], whereas actual industrial applications of the KF in six fields of the industrial electronics community are reviewed in the next sections.

III. Sensorless control, diagnosis, prognostic health monitoring and fault-tolerant control of AC drives

A. Motivation and background

As in many application fields, KF have been used for over twenty years in intelligent electrical drives for state variable estimation. Nowadays, standard requirements for industrial drives of induction motors (IM) or permanent magnet synchronous motors (PMSM) include sensorless speed control, which means that the system can be used without a position sensor [14], [15]. The advantages of speed/position sensorless control are reduced hardware complexity, lower cost, reduced size of the machine drive, elimination of the sensor cable, better noise immunity, increased reliability and lower maintenance requirements. Moreover, a motor without a position sensor is more suitable in case of harsh operating environments.

For this, the rotor speed or position has to be estimated, and many methods are now available. Numerous estimation methods have been developed so far, based on various techniques, like signal injection, based on rotor saliency, or algorithmic methods, based on a motor mathematical model or on a black box model [14]–[22]. Model-based methods are sometimes called Fundamental Wave Models [17]. Among the algorithmic methods, some are using state estimators, including MRAS (Model Reference Adaptive System) [18], or state observers, based on a deterministic approach [14]–[16], [19]–[21], while others are using a stochastic approach based on extended Kalman filtering (EKF), which will be discussed in details in the next subsections.

B. Overview of sensorless control for IM

Some of the first applications of EKF for the rotor flux and speed estimation as well as for the rotor flux and rotor time constant estimation for IM drives can be found in [23], [24] and [25], [26], respectively. In these works, only simulation results were presented.

In the first research works concerned with rotor flux and speed estimation [23], [24], [27]–[29], the motion equation of the drive system was omitted in the model used to build the KF, and the motor speed was considered as a randomly varying parameter. This led to a significant speed estimation error during transients, particularly during instantaneous load variations, although the performance was improved in steady state. A similar approach was used in [30], [31], where a reduced-order EKF was applied for the rotor flux and speed estimation.

All these methods provide an estimation of the rotor flux and speed based on the assumption that there is no change in the resistances of the motor windings. Similarly, none of these studies estimated the load torque, thus the proposed solutions showed some sensitivity to the variation of those parameters. The state vector of the IM was extended to the rotor time constant for the first time in [25], proposing a simultaneous state and parameter estimation.

The rotor resistance was also estimated in [32]. However, the rotor resistance estimation was performed by the injection of low-amplitude high-frequency signals into the flux reference in the direct vector control of the IM, causing fluctuations in the motor flux, torque, and speed.

Another approach was developed in [33], where the authors estimate the motor speed by taking the motion equation into consideration for the design of the EKF. The authors also propose to estimate the rotor resistance and mechanical load torque, thus demonstrating improved results over a wide speed range. However, these results are sensitive to stator resistance variations, indicating the necessity of an approach to estimate both winding resistances of the motor as well as the load torque.

Studies achieving the simultaneous estimation of stator and rotor resistances in the sensorless control of IMs are very few and show well-known difficulties in steady state, due to a lack of identifiability of the IM model parameters. Several approaches combining extended state observers, neural networks, high-frequency signal injection methods or MRAS techniques with switching models depending on the actual operation state of the drive, were proposed, e.g. [34]. The main drawback of these techniques is that the algorithm identifying the resistances can only be used when the sensorless speed control system is in steady state and not when the load torque is largely varying or when the speed reference is changed. So the proposed solutions can compete with a speed-sensor-equipped drive only if accuracy in steady state is not essential and operation under high loads and low speeds is not a requirement.

Studies achieving the simultaneous estimation of stator and rotor resistances for the sensorless control of IMs was reported in [35], where two EKF algorithms were consecutively used at every time step, without the need for signal injection or for algorithm changes, as in most previous studies. This technique was called a “braided” technique. The two EKF algorithms have exactly the same configuration and are derived from the same extended model, except for one state, namely the stator resistance in one replaced by the rotor resistance in the other. The braided EKF technique exploits the persistency of excitation required for parameter convergence in steady state, fulfilled by the system noise (or modeling error), as well as the fast convergence of EKFs. An improvement of this technique was reported in [36], where a so called bi-input EKF was proposed. This algorithm consists of a single EKF algorithm using consecutively two inputs based on two extended IM models developed for simultaneous stator and rotor resistances. Such a solution, requiring less memory and computation time, is more suitable for real-time implementation

C. Overview of sensorless control for PMSM

Thanks to their ability to perform state estimation of nonlinear systems, EKFs have also found wide application for the estimation of rotor position and speed in synchronous motor drives. Initial attempts to combine flux linkage and position estimation for brushless PMSM machines were frustrated by the real-time processing power available at that time [37]–[39]. Subsequent advances in DSP technology have allowed these estimation principles to be effectively implemented in [40], [41], including stator-resistance estimation joined to an algorithm to counter the effects of flux-linkage estimation errors caused by an incorrect value of resistance as the motor temperature rises during continuous operation.

Although last generation floating-point DSPs can easily overcome the EKF real-time calculations, they are not suitable for low-cost PMSM applications. Moreover, long computation requirements disturb other program service routines such as fault diagnosis or custom programs implemented in industrial products. Therefore, some efforts have been made to reduce the computation time of EKF algorithms for PMSM by using a reduced-order EKF [42]–[44]. A third-order EKF using back-EMF detection algorithm is also proposed in [42] and [43], but the output state equation used is complex. In [43], a second-order EKF is proposed to estimate stator resistance and flux linkage, but not for a sensorless control purpose.

Some recent achievements on the use of EKF for online estimation of state variables in sensorless IPMSM control applications are reported in [45], [46]. In [45], the EKF is used for the permanent magnet flux identification of an IPMSM, combined with a rotor speed and stator resistance estimation performed with an MRAS technique. The authors showed that the convergence and stability problems generally encountered when simultaneously estimating the flux, speed and stator parameters are avoided this way. In [46], the ease of implementation and the robustness to parameter uncertainty of an EKF and of an adaptive sliding-mode observer are compared. The authors claim that for IPMSM drives, this latter solution is much simpler.

EKF has also been proposed for the joint estimation of mechanical variables and parameters of systems with complex mechanical parts, including elastic couplings [47]–[52]. In these works, the estimation of the load side speed, torsional and load torque as well as the load side inertia have been estimated effectively, using linear and nonlinear EKFs. In [49], an original method was proposed for the simultaneous estimation of mechanical state variables and of the load side inertia. The elements of the covariance matrix Q are adapted according to the estimated value. In [50], [51], an evolutionnary algorithm associated with a μ-analysis for the stability analysis of the closed-loop system was used to tune the observer and controller. The μ-analysis theory helps to cancel known unstable set of parameters before running iterations in the optimization algorithm.

D. Diagnosis, prognostic health monitoring and fault-tolerant control overview

In order to guarantee a safe and efficient operation of control systems against various failures, computer-based failure detection algorithms have been developed. Various approaches have been applied, i.e. observer-based techniques, artificial intelligence techniques, etc. In this context, the KF has played a major role. See for example [25], [25], [53]–[55].

The KF relies on a system model with uncertainties that are assumed to be Gaussian white centered random variables with known covariance properties. Nevertheless, this assumption is not generally satisfied and the tuning of the covariance matrices is not obvious. This point is especially sensible for diagnostic. In fact, the covariance matrices can provide information about the quality of the estimates. However, if the covariance matrices of the noise and state are not well defined, the estimation error covariance matrix is therefore meaningless. In practice, two methods exist for the tuning of the KF: the first one relies on the evaluation of the state and measurement noises, allowing to assess the quality of the estimates with the covariance matrices. Yet, this approach is often difficult, if not impossible [53]. The second one relies on the tuning of the dynamic convergence with or without autotuning methods [35], [44], [56]–[58]. In practice this latter method is often used. In [49], [59] some guidelines for a more systematic way of covariance matrix selection have been proposed, including genetic algorithms. Therefore, the evaluation of the covariance matrices Q and R which take into account the physical approach, i.e. the model approximation (discretization, parameters’uncertainties) and the measurement noises (quantification error) is still an open issue.

The conventional KF and its extended version have become a standard tool in the last 40 years. Generally, diagnosis leads to parameter estimation and the problem is often non-linear. The linearization of the non-linear system allows to apply the conventional linear KF. However, the performance of the EKF decreases when the system includes strong non-linearities. In such cases, designers prefer to use unscented Kalman filters (UKF) for their superiority [10], [60]–[63].

Diagnosis has recently been extended to fault-tolerance control. Monitoring and controlling systems under a wide variety of faults is more and more mandatory. Several failures may occur in electrical systems and so far, redundant or conservative designs have been used in applications in which continuity of operations is a key feature. This is the case for aircraft control, home and civil appliances (such as for example gas turbines [64], air conditioning/heat pumps [62], engine cooling fans, and electric vehicles [65]), where reliability is a key issue. The objective of fault-tolerant control is to propose solutions that provide fault accommodation to the most frequent faults and thereby reduce the cost of handling them. In submerged pumps or hostile environments where accessibility to the drive and to the sensors is tedious and continuity of operations is nevertheless mandatory, even in case of fault occurrence, a sensorless algorithm is essential to maintain the availability and therefore increase the reliability.

In [65], the authors presented and experimentally tested a PMSM drive which is robust to mechanical sensor failure. In order to increase the reliability, two virtual sensors (a two stage Extended Kalman Filter (OTSEKF) and a back-emf adaptive observer (AO)) and a Maximum Likelihood voting algorithm are combined with the actual sensor to provide a fault tolerant controller. Fig. 1 shows the results of the fault tolerant controller where the outputs of the voting algorithm are used in the Field Oriented Controller. For these operating points, the OTSEKF is engaged in the sensorless controller when a position sensor fault appears. The transitions between the sensor outputs and the estimations are smooth. The errors between the estimated and the actual position and speed are small and confirm the validity of the FTC. The lower curves represent the stator currents i_{sd} and i_{sq}, where neither oscillations nor spikes are observed during the switching modes.

Today, diagnosis is extended to prognostic health monitoring (PHM) to accelerate the estimation of faulty conditions. PHM has been applied to AC machines in order to detect as soon as possible damages such as broken bars, unbalanced stator supply, etc. Generally, an off-line polynomial approach is used, based on a database of healthy and faulty modes. The evolution function is defined as

$$x = A + B\mu + C\mu^2 + \dots \tag{20}$$

where x is a vector composed of n features of the machine (i.e. current mean power, direction of the current vector, etc) and μ is the severity degree. However, this method doesn't take into account new measurements and the parameters variations. This is the reason why observers are best suited for such purpose. In [66], a KF has been designed to estimate the evolution of the number of broken bars or the unbalanced stator supply of an induction machine. The proposed method consists of two steps: i) an update of the state space model at time k, ii) a prediction of the state at time $k+n$. Therefore, this method consists in determining the best parameters of the state space model before beginning the prediction, and the use of an observer recursively increases the knowledge as new measurements are received.

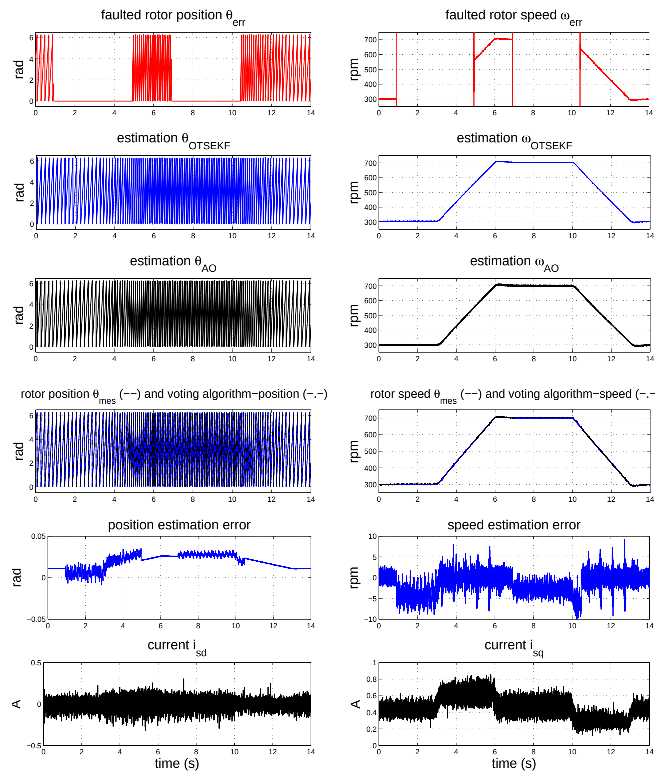

Fig. 1. Experimental results of a PMSM fault-tolerant controller in the event of a power failure at no load from paper [65] (A. Akrad, M. Hilairet and D. Diallo).

Fig. 2 shows one result for the prediction of the unbalance stator supply presented in [66]. It clearly shows that the KF prediction of a 40% unbalanced stator supply is close to the real value, compared to a conventional polynomial approach.

E. New trends

One key issue to sensorless control of AC drives, fault detection, diagnosis and isolation (FDDI) mechanism is related to

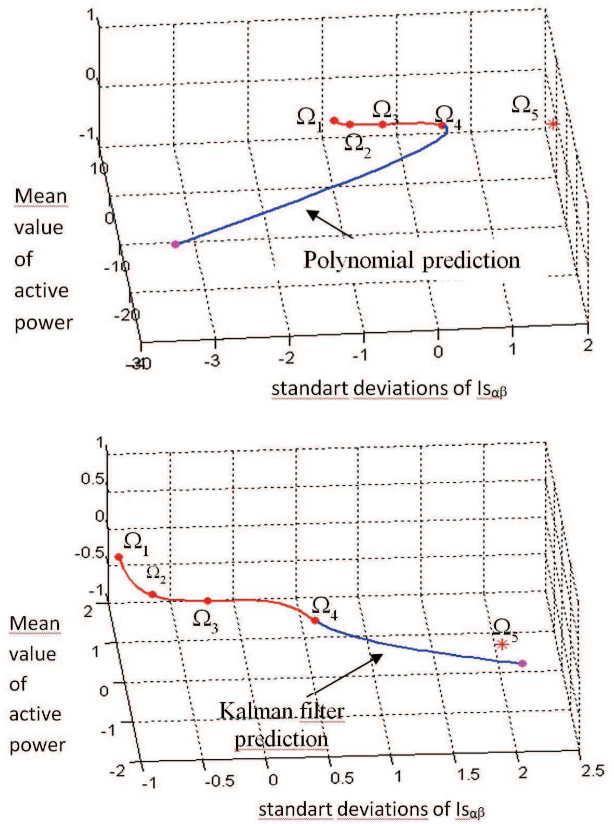

Fig. 2. Extrapolation and estimation with a KF from paper [66] (O. Ondel, E. Boutleux, E. Blanco, G. Clerc). Ω_1 healthy mode, Ω_2 unbalance stator supply 5%, Ω_3 unbalance stator supply 10%, Ω_4 unbalance stator supply 20%, Ω_5 unbalance stator supply 40%.

observability. Deterministic or stochastic model-based methods are all more or less sensitive to parameter variations and cause problems with observability and stability at low speed or in regenerative operation mode. The operating conditions must excite the system in the frequency range of the parameters to be identified. However, operating conditions may lead to the unobservability of some variables or parameters. For a stator frequency close to zero, the induced rotor voltage takes very small values and thus the estimation of the speed of an IM [67] or the estimation of the rotor position of a PMSM [68] becomes impossible. In addition, the simultaneous estimation of the rotor speed and the rotor resistance of an IM fails under constant flux operation or at no-load condition in steady state with a very low and zero speed [25], [54]. Therefore, monitoring the thermal behavior of the induction machine in real time is difficult [55], because secondary phenomena (such as parameter uncertainties, signal acquisition errors and noise at the very low speed range) are not taken into account in the machine model used for the estimator design. Moreover,

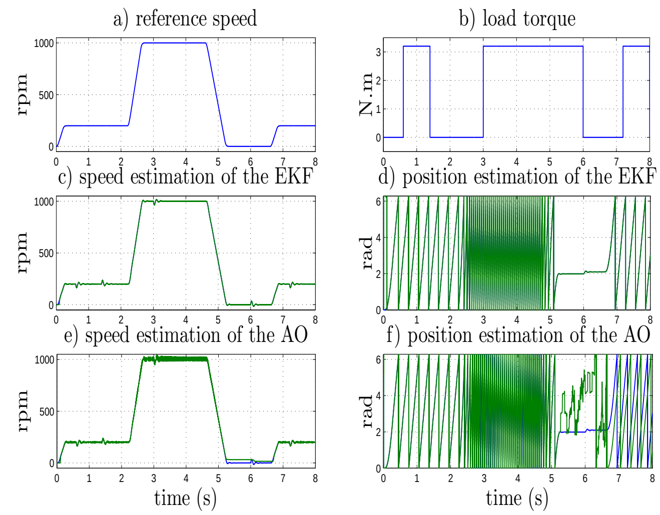

Fig. 3. Position and speed estimation of a PMSM with a EKF and an adaptive observer.

in steady state at zero speed, the input variables of the motor (stator currents) do not satisfy the PE (Persistent Excitation) condition. In practice, the KF seems to operate well in such conditions without any divergence compared to extended Luenberger observers, sliding mode or adaptive observers where the gains go to the infinity. These observations need further investigation, in particular for fault-tolerant control against position sensor failure [65]. To illustrate this observation, an EKF and an adaptive observer were compared in [65] for the position and speed estimation of a buried-mounted magnets synchronous machine according the benchmark defined in Figs. 3.a and 3.b. Figs. 3.c and 3.e show the speed estimations when the motor speed is considered as a constant value for the design of both observers. These figures show that both observers have the same tracking capabilities, but the EKF doesn't fail at zero speed and rated torque compared to the adaptive observer, as shown in Fig. 3.f.

To overcome the unobservability of model-based methods, high-frequency signal injection has been introduced for IM as well as PMSM drives [14], [15], [17]. However, some consider that the requirement to superimpose additional AC components to the input signals of the estimator can be overcome by the use of a non-deterministic approach based on Kalman filtering. Model uncertainties and nonlinearities inherent in AC motors as well as signal noises are well suited to the stochastic nature of the EKF, which is basically a recursive observer providing an online state and parameter estimation of a nonlinear dynamical system from noisy measurement signals in a wide speed range [35], [41], [53], [56], [69]. The EKF is also known for its high convergence rate, which significantly improves performance during transients. These properties are the major

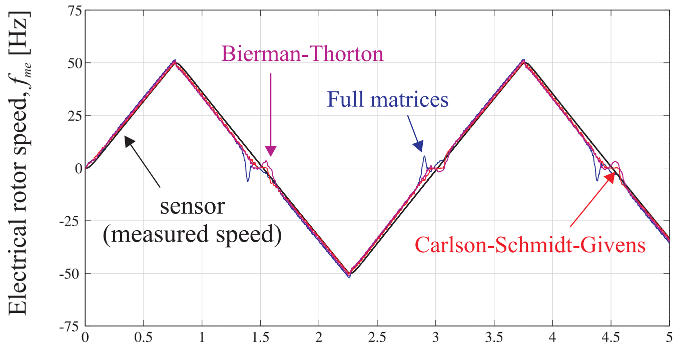

Fig. 4. Simulation results from paper [69] (V. Smidl and Z. Peroutka). Electrical rotor speed estimation error for all investigated EKF algorithms.

advantages of the EKF over other estimation methods (e.g. high-frequency signal injection methods) and are the reasons why this method finds a wide application in sensorless state variable estimation, in spite of its computational complexity (and relatively long computation time), which is a disappearing problem with the recent developments in high-performance processing technology (see section VI). Therefore, data fusion of estimates from model-based methods and high-frequency signal injection methods such as in [70] could be a promising trend.

Moreover, the robustness of the "observer+controller+process" system is still an open issue. In fact, the estimates could be used in the controller in order to optimize the whole system performance. Generally, this leads to the interconnexion of non-linear systems, thus the stability of the whole system is not trivial.

Finally, numerical stability issues of the KF are well known. Better numerical stability can be achieved by using square root decompositions [11]. Two widely used factored form of the KF are used in order to reduce these phenomenons, i.e. the UD and RC decompositions [11]. These forms improve the estimations accuracy and decrease the risk of divergence. The computational time consumption, estimation accuracy and instability of the KF are also still open issues. New high level theoretical and applied researches are regularly published, such as [69], [71], [72], and see [11] for survey.

Fig. 4 shows the results of a fixed-point implementation of the EKF used for the sensorless control of a PMSM drives presented in [69]. Three square-root algorithms, namely the Bierman-Thorton, Carlson-Schmidt-Givens, and Carlson-Schmidt-Householder algorithms, have been implemented and compared on both simulation and experimental results. The performances of the 3 algorithms were evaluated and compared to a regular implementation based on full covariance matrices. It was confirmed that the square-root algorithms improve the behavior of the sensorless control in critical operating conditions such as low speeds and speed reversal. In particular, the Carlson-Schmidt-Givens algorithm was found to be relevant for the considered drive.

IV. Distributed Generation and Storage Systems

As shown in the previous sections, Kalman filters have been used for a long time in electrical engineering applications such as parameter estimation of electric machines [25], [73]. The application of KF and EKF in new electrical concepts such as distributed generation and storage systems is presented in this section.

A. Distributed Generation and Microgrids

Kalman filters have also been used previously in power electronics control applications like fundamental voltage waveform tracking at the point of common coupling (PCC) of distributed generators (DGs) forming a microgrid system [74]. One application consists in using Kalman filters in the current control loop of grid-connected inverters as a way to cancel the current harmonics injected to the grid [75]. Some examples of PLLs based on Kalman filters are presented in order to quickly estimate the amplitude and the frequency of the grid [74]. The Kalman-filter can be used to transform the current signals into ideal sinusoidal waveforms, in spite of the grid-voltage distortion. These signals are the inputs of PLLs to be transformed to the synchronous reference frame, thus ensuring a fast low distorted operation of the PLL [74].

B. Energy storage systems

Another important application is the estimation of the state-of-charge (SoC) of batteries used in energy storage systems [76]. Hybrid Electric Vehicles (HEV) for example require Battery Management Systems (BMS) that should be able to estimate the battery SoC, the capacity fade and the available instantaneous power. Such an estimator must adapt to changes caused by aging in the characteristics of battery cells, and must provide an accurate estimation of their lifetime, which highly depends on the user's driving style. It should be noticed that the terminal voltage adopted in this kind of applications is not the open-circuit voltage, which is commonly used in off-line SoC estimation. The relationship between the terminal voltage and the SoC is supposed to be

$$V_{\mathrm{out}} = k_0 - \frac{k_1}{\mathrm{SoC}} - k_2\mathrm{SoC} + k_3 \ln(\mathrm{SoC}) - R\, i_{\mathrm{out}} \tag{21}$$

where i_{out} is the output current, R the output impedance, and $k_0,\ldots,\ k_4$ are some coefficients.

The SoC can be estimated by using the Coulomb counting method, which is based on the fact that the energy contained in an electric charge is equal to the integral over time of the

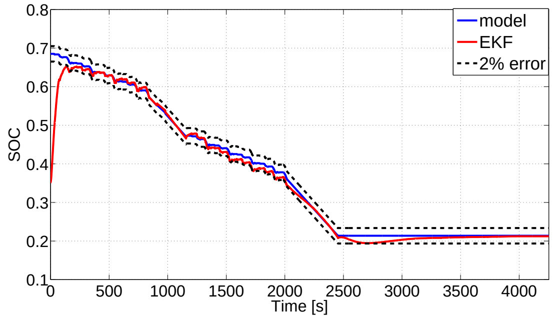

Fig. 5. SoC estimation for an urban/suburban driving cycle from paper [80] (D. Di Domenico, Y. Creff, E. Prada, P. Duchêne, J. Bernard, V. Sauvant-Moynot).

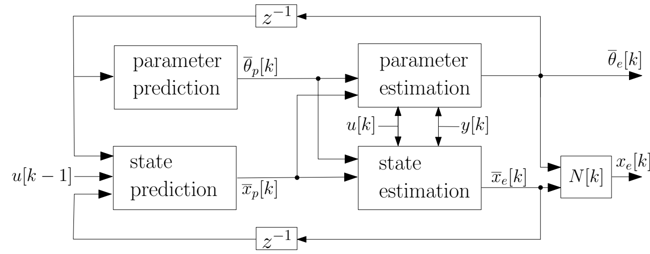

Fig. 6. Two-stage EKF.

current delivered to the charge. Thus, the battery mathematical model of Coulomb counting can be expressed as

$$\frac{d}{dt}\text{SoC} = -\frac{\eta}{C_n}\, i_{\text{out}} \tag{22}$$

where η is the efficiency of discharge and C_n is the nominal electric capacitance of the battery. Eq. 21 and 22 constitute a dynamic model of the battery, Eq. 21 being the measurement equation and Eq. 22 being the state equation. The input signal of this system is the current i_{out} and the output signal is the terminal voltage V_{out}, while the SoC is the only state variable. However, there are some problems with the above mathematical battery model. The first one is that data-fitting algorithms cannot give results in real time. A second one is that the coefficients in eq. 21 depend on the ambient temperature. Experimental data obtained in a laboratory are obtained for one temperature condition only. In a practical application, temperature may change continuously. As a result, we need to find a strategy to estimate the instantaneous SoC. The conventional Kalman filter [77]–[80] can be a good solution for the online SoC estimation, because it tries to get accurate information from non-accurate data. In a series of three papers [78], a method based on Extended Kalman Filtering (EKF) was proposed. This method is applied to a Lithium-Ion polymer battery pack, taking its nonlinearities into account.

Fig. 5 shows a result presented in [80] of the SoC estimation provided by an EKF, compared to a correctly initialized Ah counting. This figure shows that the EKF converges quickly to the real value, although the initial value of the SoC is underestimated by 35%, and that the steady state error is lower than $\pm 2\%$.

In the same spirit as the new trends presented in section III, Unscented Kalman Filter (UKF) has also been applied to self-adjust the model parameters of the battery and to provide a better SoC estimation [81]. As stated in section III.D, the main drawback of the KF is the importance of a good determination of the Q and R matrices, that are not accurately known in practice. To improve the performance of the KF for SoC estimation, an adaptive EKF can be designed, so as to estimate the covariance matrice [82].

Finally, the computation time and divergence of the KF are still issues for such embedded applications. Generally, the temporal equation of the estimated parameters $\theta[k]$ is unknown and therefore leads to a dynamical model as follows [83]:

$$\begin{aligned} x[k] &= f(x[k-1], \theta[k-1], u[k-1]) + W^x[k] \\ \theta[k] &= g(\theta[k-1], u[k-1]) + W^\Theta[k] \\ y[k] &= h(x[k], \theta[k], u[k]) + \eta[k] \end{aligned} \tag{23}$$

Based on the fact that $x[k]$ is not used in the prediction equation of $\theta[k]$, [78] proposes the application of a dual extented Kalman filter for joint state and parameter estimation. Furthermore, alternative approaches can be used to enhance parallel execution such as interleaved EKF [84] or multi-stage EKF [83], [85] (see Fig. 6).

V. Applications in Signal Processing, Instrumentation, Robotics and Vision

A. Applications in Signal Processing and Instrumentation

Within the Signal Processing community, Kalman Filtering remains a very active topic. Contrary to what some people say, new high level theoretical researches are regularly published, such as [86]–[90]. Some of them focus on the approximation of the first- and second-order statistical moment of a nonlinear transformation of a random variable, a key problem for the estimation of the state of nonlinear dynamic systems. Recent applications of Kalman Filtering have also been published in a very large diversity of subjects: identification of time series models (AR, ARMA, sum of sinusoids ...), moving target localization and tracking, denoising and signal enhancement, deconvolution, wireless sensor networks and distributed estimation, biomedical applications, to name but a few.

Instrumentation is of course one of the main purposes of Kalman Filtering. In this area, several recent publications have shown the benefit to use Kalman filters for sensor fusion, sensor calibration, frequency measurement, ultrasonic time of flight estimation, network-based clock synchronization and Global Positioning Systems, among many others.

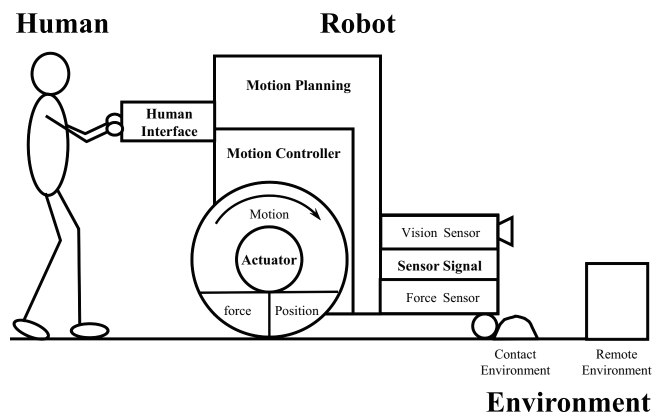

Fig. 7. Human-robot interactions in open environment.

B. *Applications in Robotics and Vision*

Kalman filtering technology is also applied to robotics and vision. Future human-robot interaction will need sensor networks. To obtain effective information from various sensors, Kalman-filter-based sensor integration has been very much researched [91]–[99]. An in-depth survey on the use of Kalman filters for vision based mobile robots is presented in [100]. Such intelligent machines and robots are required to have abilities of recognition and adaptation to open environment. Human-robot interactions in open environment are considered as shown in Fig. 7. In an open environment, robots are expected to cooperate and support human where the environmental situation is changed momentarily.

Since the environment may have infinite modes, it is necessary to classify modes for which a robot must be adapted. It is natural that environmental modes should be classified according to the distance between a robot and its environment. To adapt to close environment, a robot should have haptic ability. This means that the motion control should be based on force control. On the opposite, a robot has enough time to adapt to remote environment. It becomes possible to design the motion control relying on position control, and its references are generated by a motion planning layer.

From the motion control point of view, it is very important to construct robust control. Feedback control of fine information from sensors decides the performance of robust control. Since robust motion controller is based on acceleration control [101], an acceleration sensor is useful to obtain wideband internal information of a robot. Generally, the bandwidth of an acceleration sensor does not cover the dc range. Thus, the position sensor information and the acceleration sensor information are integrated to cover from dc to a larger frequency band range. It is possible to obtain wideband acceleration information with a Kalman filter. As a result, purity of the acceleration information makes a motion control system using a disturbance observer more robust [102].

On the opposite, from the motion planning point of view, it is important to recognize the outer environment. A measurement of the relative distance is necessary for controlling a mobile robot. Especially, simultaneous localization and mapping (SLAM) has been widely researched [91]–[95]. Vision systems are useful for the perception of remote environment [96].

In addition, recognition of human motion is also an important issue for future human support. For such purposes, sensor fusion techniques based on Kalman filtering are researched widely [97] [98]. Once human motion is acquired by sensor fusion and stored in a motion database, skilled experts can reproduce it at anytime and anywhere. Recognition, preservation and reproduction of human motion will have a wide area of applications, such as skill tele-training, skill transfer, and so on.

As stated above, sensor fusion techniques will be widely applied in future robotic applications. In particular, constructing a sensor network is more and more important for future human support technology. Sensor networks and robotic systems will support and extend human physical activities.

VI. Real-time implementation of a Kalman filter for industrial control systems

A. *Overview*

Due to its high computational complexity, the digital real-time implementation of the Kalman filter has always been a challenging issue. The three main difficulties that have to be addressed are:

- The minimization of the effect of the computational roundoff errors on the stability of the Kalman filter, when computing the covariance matrices.
- The reduction of the computational load of the Kalman filter.
- The minimization of the execution time of the Kalman filter.

To address these issues, two types of solutions are possible:

- The modification of the algorithm to be implemented.
- The use of an efficient digital architecture to implement the estimator, being either a processor or a dedicated hardware architecture.

In this section, a brief description of the above mentioned issues will be presented along with the possible solutions to tackle them. Practical references will be given to help the reader to go further. To illustrate our presentation, a special attention will be given to a popular estimation case in the field of industrial electronics. It consists in the estimation of mechanical quantities of an AC drive. The above mentioned issues are of course not the only ones that can impact the performances of a Kalman filter. Determination of the noise covariance matrices, as well as the initialization of the covariance matrices, are also key-elements of a Kalman filter tuning. However, the errors made in the choice of the parameters of these matrices are much more related to the poor knowledge that the designer has on the actual system rather than rounding errors. That is the reason why these points will not be discussed further in this section.

B. Effects of computational roundoff errors on Kalman filter performances

Since the early ages of the Kalman filter, engineers have observed the high sensitivity of the Kalman filter with regard to the roundoff errors in the computation of the covariance matrices, which are the solution of a matrix Riccati difference equation [11]. Indeed, due to roundoff errors, this matrix can lose its symmetry and can also have a negative eigenvalue. All these phenomena have a direct impact on the Kalman gain and, as a consequence, slow down the convergence of the estimator. One way to make the numerical solution of the Riccati equation more robust against roundoff errors is to use factorization methods (Cholesky or modified Cholesky factor decomposition). These methods are also known as square root filtering. Several decompositions have been proposed which differ in the way the factorization is achieved [11]. The additional cost in terms of computational load has of course to be taken into account [103], but the gain in terms of robustness of the filter is significant. In a recent paper [69], the authors have compared the implementation of a sensorless PMSM drive on a low cost 32b fixed-point TI DSP (TMS320F2812) using three different square root algorithms. It has been demonstrated that the Carlson-Schmidt-Givens algorithm offers the best compromise between performances and execution time.

As mentioned in the introduction, numerical issues can also be addressed by using powerful hardware architectures. Thus, an accurate implementation of a Kalman filter on a floating-point DSP is also another natural way to reduce the impact of computational roundoff errors [40], but the counterpart of using such a processor is a significant increase of the execution time and an increase of the hardware cost.

C. Reduction of the computational load

The computational load of a Kalman filter is an important issue for at least two main reasons: the number of arithmetic operations to be executed at each sampling period, which is in $\mathcal{O}(n^3)$ [104], and the nature of the operations (additions and multiplications of matrices and most of all, one matrix inversion). Therefore, researchers have naturally tried to reduce the computing load by taking benefits of the specificities of the matrices involved in the algorithm (symmetries, sparsity). Thus, in [56], the authors have reached a cost reduction of 2.7 compared to the standard solution for a 5th-order Extended Kalman filter used to estimate the speed and flux vector components of an induction motor. A similar approach was recently proposed in [105] for a 4th-order Kalman filter used to estimate mechanical quantities of a synchronous motor. In this case the implementation was achieved in a Field Programmable Gate Array (FPGA). However, a direct consequence of these searches or specificities in the matrices involved in the filtering process is an increase of the development time.

To reduce the computational cost, the KF can also be subdivided into parallel KFs, so called “multi-stage Kalman filter” or “inter-connected Kalman filter”. In 1969, Friedland [106] introduced for the first time a two-stage Kalman estimator. The main idea is to decouple the Kalman filter into two parallel filters: a full-order filter and another one for the augmented state. The computational cost is reduced by computing two small inter-connected Kalman filters rather than a full Kalman filter although the algorithms are performed sequentially. Therefore, the two-stage Kalman estimator has added a new dimension to the design of algorithms and architectures.

Friedland’s filter is devoted to the estimation of the state of a linear process in the presence of a constant but unknown bias vector; so many researchers have contributed to this area in order to extend this approach [107]–[110]. In 1999, Hsieh and Chen [108] proposed an optimal two-stage Kalman estimator that recovered the performance of the regular Kalman filter. This modified Kalman filter is “optimal” in the sense that the equations are mathematically equivalent to the regular equations of the Kalman filter. Later, this optimal two-stage Kalman estimator has been extended to general non-linear systems [110].

Effective implementation of interconnected KF in the AC drive community are related to sensorless speed control of induction machines [83] and fault-tolerant control of permanent magnet machines [65].

D. Minimization of the execution time

Nowadays, most of the digital implementations of Kalman filters for industrial systems are using DSP components. Indeed, these components are well-adapted to intensive matrix/vector computation by integrating a multiply and accumulate ALU. Thus, in [73] was presented one of the first DSP-based implementations of a Kalman filter for sensorless permanent magnet synchronous drive. A 4th-order EKF was implemented in a fixed-point TI TMS 320C25, with a total execution time equal to 283.5 μs. Around eight years later, Bolognani et al. [40] implemented a similar algorithm on a much more powerful floating-point TI DSP in only 143 μs.

However, in order to drastically decrease the execution time of such complex estimators, designers have no other options than parallelizing the tasks that can be executed concurrently. Along this line, since the early nineties, some authors proposed systolic array implementations of the Kalman filter [111], [112]. A systolic architecture consists in a highly regular, parallel, pipelined and expandable array of simple operators with only local data transfers. Based on advanced concepts of applied mathematics, the proposed systolic arrays were potentially powerful (with high computing density), however only a few implementations were actually achieved. This was due to the necessity of implementing systolic arrays in dedicated silicon components (Application Specific Integrated Circuit, ASIC) which are known to be very expensive solutions. Besides, they were also found to be poorly flexible and as a consequence difficult to re-use in other applications than the one it was designed for. However, a renewal of this approach is possible due to the ever increasing capacities in terms of resources of FPGAs and their flexible development tools.

Indeed, with FPGAs, designers have the possibility to easily implement a dedicated hardware architecture that matches the salient features of an algorithm. Thus, significant reduction of execution time can be achieved [113]. The first implementation of a Kalman filter in an FPGA was published in [114]. It was designed as a co-processor, also termed as hardware accelerator. It was applied to a 4th-order multi-tracking radar system. The obtained execution time was equal to only 0.4μs. Even if the model of the studied plant was quite simple, the result in terms of execution time is by far lower than any programmed solution. This was due to the design of a fully hardware parallel architecture. Implementing a dedicated hardware parallel architecture is the main advantage of using FPGAs compared to processor solutions in order to accelerate computation. Besides, this kind of hardware architecture can now be easily programmed using Hardware Description Languages (HDL) or directly from Simulink via the use of specific toolboxes (DSP Builder from Altera or SysGenerator from Xilinx). In [115], authors presented and tested experimentally an FPGA-based extended Kalman filter for a sensorless synchronous motor drive. The EKF execution time is equal to 2.8μs only on a low-cost Spartan 6 FPGA. In addition, it was also demonstrated that the reduction of the speed estimation time increases the bandwidth of the speed loop, as can be seen on Fig. 8. This gain is all the more important that the base speed of the motor is high, as in aircraft applications.

Finally, full hardware or software implementations of the Kalman filter are not the only solutions available today. Indeed, designers have also the possibility to take benefits of the recent, very powerful and low cost FPGA-based System-on-Chip platforms to implement sophisticated Kalman filter algorithms. Since recently, it is now possible to find on the market a component which includes a dual hardware core ARM9 processor along with a dense FPGA fabric (tens of thousands of logic cells, hundreds of DSP units and memory blocks). The design challenge in this case is to find an optimized partitioning between the tasks to implement in software and those to implement in hardware. Along this line, a Hw/Sw partitioning of a EKF for drive applications optimized by a genetic algorithm has been recently presented in [116]. One of the main interest of this study was to integrate heterogeneous constraints at the early stages of the optimized partitioning process. These constraints include both control constraints (phase margin and bandwidth of the control loops) and hardware constraints (resources of the FPGA fabric, memory space).

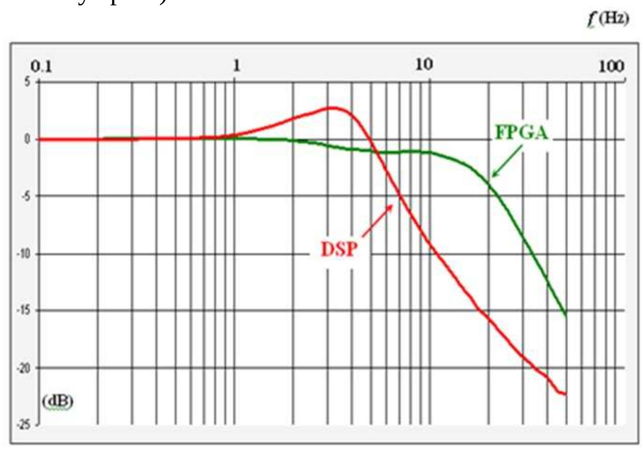

Fig. 8. Magnitude of the frequency response of the speed loop of a 200 kVA aircraft Brushless Synchronous Starter/Generator.

VII. Conclusion

This paper has summarized the research efforts made over the past two decades about the application and the digital implementation of Kalman filters in a significant number of industrial fields. In summary, one of the main issues of this recursive state estimator was the computational load requirement. Therefore, two research directions have mainly been investigated. The first one, started in the 70s, focused on factorization methods and fast algorithms. This research was primarily motivated by aerospace applications. The second approach, which appeared later, focused on the design and implementation of highly sophisticated numerical architectures embedded on FPGAs.

Nowadays, the integration of Kalman filters or variants of the Kalman filter (i.e. unscented Kalman filters, etc) into industrial systems is not so widespread for two main reasons: the complexity of the algorithm compared to the classical Luenberger observers and the computational load requirement to be embedded on a low computational power processor. However, thanks to the availability of new low-cost and highly elaborate processors (such as floating point DSPs targeted at real-time process control applications, System-on-Chips, etc), the Kalman filter is likely to spread more and more and still has a bright future ahead of it.

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