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Comparative analysis of features of online numerical methods used for parameter estimation of PMSM

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ABSTRACT

As permanent magnet synchronous motors (PMSM) have high power density, efficiency, good dynamic performance, and small size they are becoming popular in electric vehicle (EV) applications. Control performance and the efficiency of the system get affected due to electrical, mechanical parameters. Parameters value gets affected by voltage source inverter (VSI) non-linearities, temperature and magnetic saturation effects. If exact parameters for particular torque speed requirement are found, the efficiency of system increases. There are various offline and online methods for finding parameters. Offline methods are easy to implement but requires extra setup and estimate parameters in steady state. Because the effects of transient conditions are taken into account during identification, online methods for obtaining real-time data under running conditions are becoming more popular. An overview about online numerical methods to estimate electrical parameters of PMSM is given. It discusses difference between various methods in terms of computational cost, convergence speed, noise and identification error. Choosing of method will be easy using this work. For inductance estimation, the extended Kalman filter (EKF) algorithm has an identification error of 0.24% under temperature effect and -0.3% under VSI non-linearities effect. The identification error for Rs and ψf using the recursive least square (RLS) method is 0.5% and 0.02%, respectively, when temperature is considered. EKF and RLS algorithms are proposed.

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1. INTRODUCTION

Permanent magnet synchronous motors (PMSM) are becoming popular in industry for electric vehicle (EV) applications [1]–[3] due to their characteristics such as high-power density, high efficiency [4], good dynamic performance, and small size [5]. There are two types of PMSMs depending upon the rotor construction-interior permanent magnet synchronous motor (IPMSM) and surface mounted permanent magnet synchronous motor (SPMSM). In SPMSM the permanent magnets are placed on the surface of rotor having equal value of d-axis inductance L_d and q-axis inductance L_q. Where as in IPMSM the placement of magnets is embedded inside the rotor [6]. Value of L_q is larger than L_d for IPMSM. Reluctance torque is present in IPMSM which gives advantage of high torque compare to SPMSM. For getting high control performance of the system, estimation of accurate motor parameters is necessary. Motor parameters can be classified into electrical parameters such as stator resistance R_s, d-q axis inductances , L_d, L_q, flux linkages ψ_f

[7], [8] and mechanical parameters like inertia J, viscous friction B_m. Generally, one gets motor parameters value by requesting manufacturer for data sheet of motor [9] and the nominal parameters like rated voltage, rated current, number of pole pairs, rated speed, rated torque, and class of insulation are available on motor's nameplate. But under running condition the effect of temperature [10], saturation [11], [12] and voltage source inverter (VSI) non-linearities [13] affects the values such as R_s, L_d, L_q, ψ_f. This affects the control performance of the system and indirectly the efficiency [14]. By getting accurate parameters, accurate control of motor can be developed [15], and efficiency can be increased. Different offline and online methods [16], [17] are available for characterization of motor. Offline methods which are available for identification of parameters are finite element method (FEM) [18], AC standstill frequency response method [19], IEC60034-4, and DC decay test [20]. In offline methods different tests are performed to get parameters [21]. Offline methods take a lot of time and require additional test settings [22]. In order to improve control performance, the EV industry is moving toward recognizing the motor parameters in real time utilizing online methods and updating the control gains of running systems. The goal is to improve system control performance.

There are different methods for online parameter estimation such as recursive least square (RLS) [23]–[28], model reference adaptive system (MRAS) [29], extended Kalman filter (EKF) [30]–[32], particle swarm optimization (PSO) [33]–[38], genetic algorithm-based methods [39], modified Jaya algorithm [40], machine learning (ML) algorithm [41], moving horizon estimator (MHE) [42], Runge-Kutta model based predictive method [43], recursive error prediction method (RPEM) [44], impedance methods [45], [46], and Gauss Newton method [47]. This paper includes different numerical methods with their characteristics and basic working process. The detailed classification of different online methods is provided in section 2.

In almost all literature field oriented control (FOC) for PMSM is considered to implement motor parameter identification. The basic principle used by FOC is that it converts stationary reference frame to rotating frame which helps to minimize the complexity of analysis. Clarke and Park transformations are used for converting the reference. Clarke transformation is used to convert three phase system (abc frame) into an orthogonal stationary frame (α-β frame). Park transformation is used to convert orthogonal stationary frame to orthogonal rotating frame (d-q frame). Most online methods from literature are using d-q reference frame for parameter identification. There is one problem in d-q frame that is 'rank deficiency'. As per the voltage (1) and (2) of the d-q frame, the observability of matrix in steady state is 2. There are 4 parameters to be identified as mentioned above, using voltage equation in d-q frame one can only find 2 parameters. Different approaches are presented to overcome this problem [21]. These depend on 2 principles: i). To decrease the number of parameter identification, and ii) To increase the rank of observability matrix. Rank of the matrix can be increased by considering various running conditions. FOC [22], [48] implementation is done using Clark and Park transformation in section 2.

This article is further organized as follows. Section 2 gives the basic mathematical model of PMSM considering the FOC and classification of parameter identification methods. Section 3 provide the different numerical methods for parameter estimation along with different features. Section 4 presents analysis in terms of identification error and comparison for various numerical methods. In identification error table percentage error considering method under some effect or no effect is provided. Finally, section 5 concludes the paper.

2. METHOD

2.1. Mathematical model of PMSM

In this section mathematical model of PMSM is introduced. By ignoring eddy current loss, hysteresis loss, magnetic saturation and assuming balanced 3 phase supply [22], PMSM voltage equations in d-q frame can be written as:

$$u_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q \quad (1)$$

$$u_q = R_s i_q + L_q \frac{di_q}{dt} - \omega_e L_d i_d + \omega_e \psi_f \quad (2)$$

where, u_d and u_q are stator voltages of d and q axis respectively; i_d and i_q are d and q axis currents respectively; R_s is the stator resistance; ω_e is angular speed in electrical reference; L_d and L_q are inductances of d and q axis respectively; ψf is the flux linkages. The (3) provides electromagnetic torque for PMSM.

$$T_e = \frac{3}{2} P_p \psi_f i_q \quad (3)$$

Where, T_e is electromagnetic torque; P_P is number of poles pairs; ψ_f is flux linkages; i_q is q axis current.

Motion equation can be given as (4).

$$T_e - T_l = J\,\frac{d\omega_e}{dt} + B_m\omega_e \qquad (4)$$

Where, T_l is load torque; J is a moment of inertia; B_m is a coefficient of friction; ω_e is angular velocity of rotor.

2.2. MATLAB model of PMSM with FOC

Figure 1 gives MATLAB model of PMSM with FOC using mathematical model of PMSM. Conversion of 3 phase to d-q frame is done using a ParkClark function. Mathematical (1), (2), (3) and (4) of PMSM are implemented for building Simulink model. Figure 2 shows the output speed waveform of the developed PMSM along with FOC control.

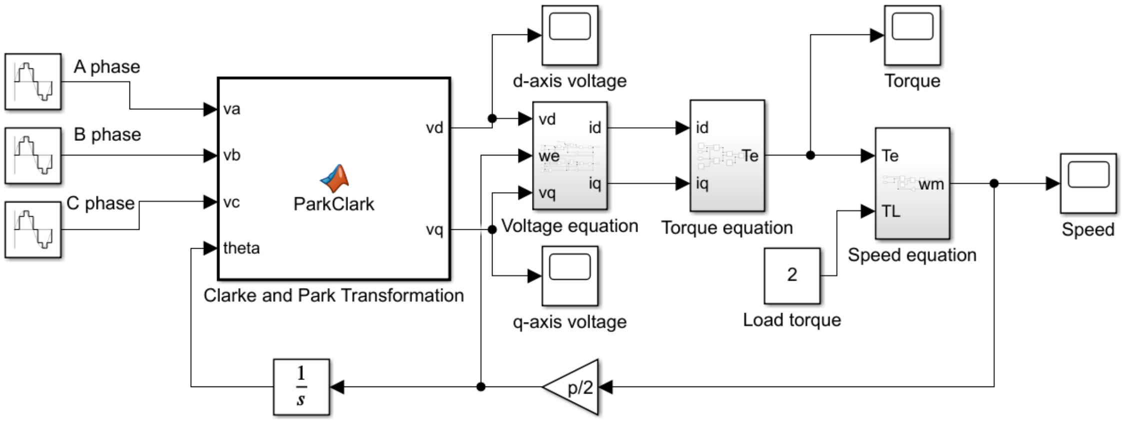

Figure 1. MATLAB Model of PMSM with FOC

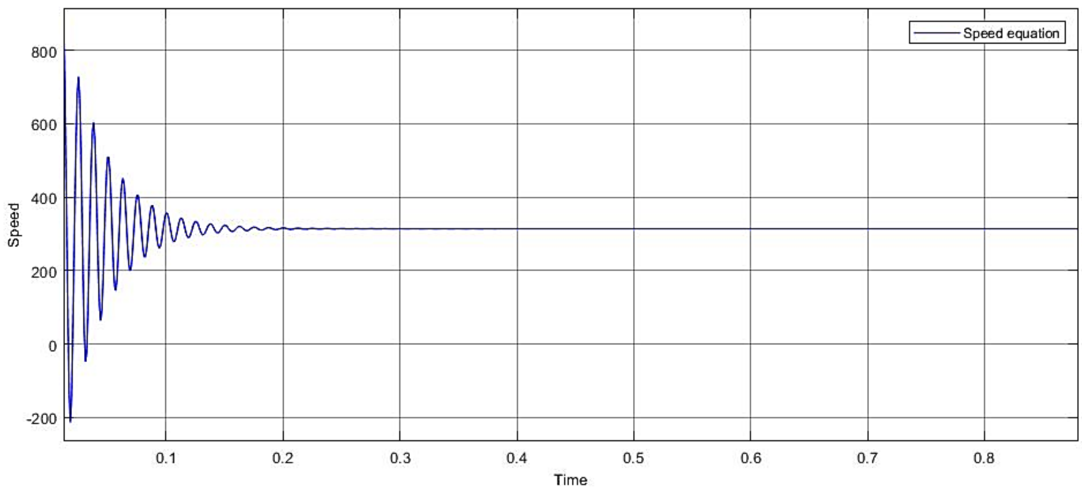

Figure 2. Speed waveform

2.3. Steps to reproduce the MATLAB model

- The Clarke and Park transformation function is written using the standard equation of conversion.
- The voltage subsystem shown in Figure 1 is developed using (1) and (2).
- The torque equation subsystem is build using (3).
- The speed is calculated using (4) and built it in speed equation subsystem.
- Constant load torque is given for operation.

– The speed is converted to electrical speed by using formula:

$$\omega_e = (p/2)\ *\omega_m$$

2.4. Classification of parameter identification methods for PMSM

There are different methods for parameter estimation. Figure 3 shows the classification of different offline and online methods. Offline methods require the extra test setup [22] and gives estimation in standstill condition. Generally, data is collected earlier and depending on that parameter are estimated. Whereas for online methods parameters are found in running conditions and hence different effects like temperature, saturation, VSI non-linearities can be considered during estimation for developing high control performance. Online methods can be classified as Numerical methods [11], [12], [14]–[32], [42]–[47], [49]–[51], Observer based methods [52], AI- ML based methods [33]–[41], [53], [54]. The focus of this article is on different online numerical methods for electrical parameter estimation.

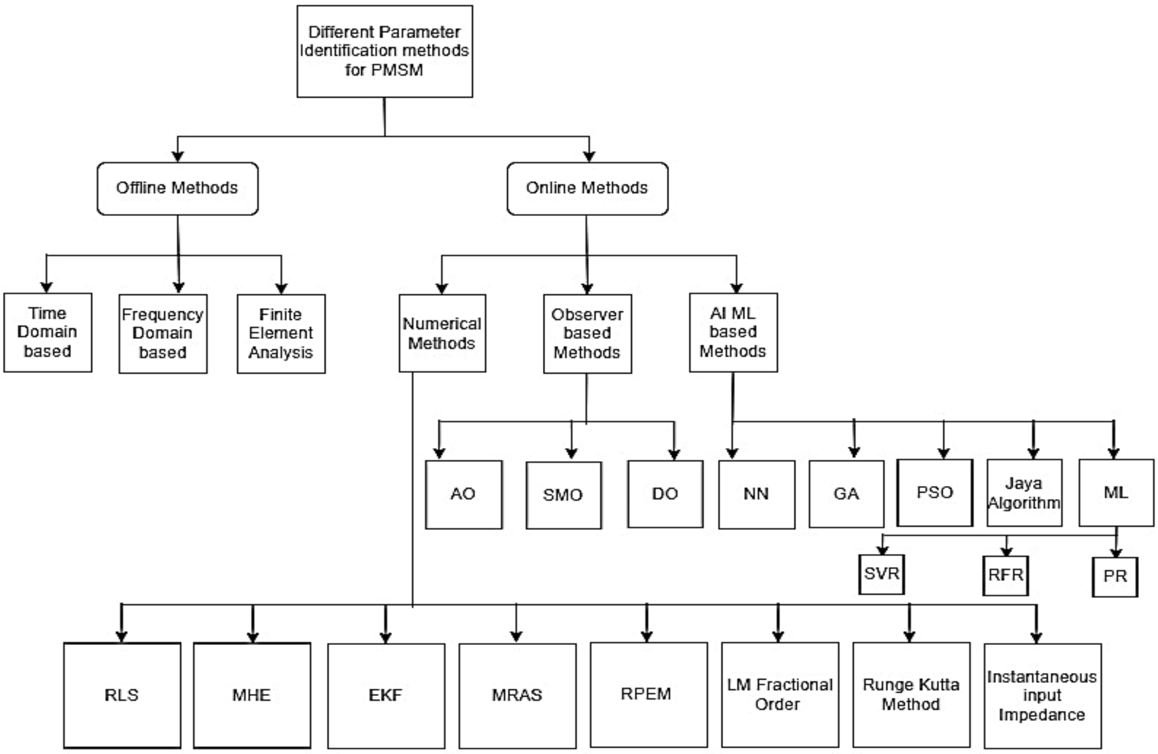

Figure 3. Classification of parameter identification methods

3. LITERATURE SURVEY

3.1. Online numerical methods for parameter estimation

In this section brief about different online numerical methods is given along with the advantages and disadvantages of it. Recursive least square method is a classical approach for parameter identification. It is used to estimate weight coefficients to minimize least square cost function [21]. Forgetting factor *f* directly affects the promptness of coefficient. Higher the value of *f*, the slower the estimation. Closer the value of *f* to one, older estimations are equally weighted. Smaller values of *f* consider only the latest measurements but increasing the value of the covariance *Q* as inferable [23]. Figure 4 shows the basic working of RLS method. Depending upon the current state and estimated state error weighted coefficients are being updated. RLS algorithm is best in steady state conditions having less execution time compared to EKF [29] and has simple theoretical derivation and implementation [23]. Apart from this it is sensitive to noise and disturbances [29]. It may not converge to accurate values in d-q frame of reference [21]. It has drawback of data saturation and has fixed gain due to which estimation accuracy gets reduced [29]. It may not perform well with low speed and light load.

Moving horizon estimation is the performance of MHE is better than Unscented Kalman Filter and EKF under transient condition. It has more accuracy compared to RLS, MRAS, EKF and Unscent Kalman

Filter (UKF) [6], [28]. Extended Kalman filter is the optimal recursive estimation algorithm based on least square method used to estimate states of dynamic nonlinear system [29]. Taylor series is used to linearize the dynamic model. For estimation, it takes measurement noise *R* and processing noise *Q* into account. Execution time for EKF is longer than RLS and MRAS [12], [17]. It is based on discrete system model of electrical system and has better optimization capability, good convergence in simultaneously estimating PMSM electrical parameters [4], [14]. Figure 5 shows the working of EKF considering the noise effects. Kerid [32] has considered temperature variation while implementing EKF algorithm for parameter estimation. Main advantage of EKF is that it rejects the process and measurement noise having similar accuracy as UKF [45], MHE. EKF with Gradient correction has small calculation, high accuracy, and fast convergence speed. It has been observed in literature that EKF has a complex structure with high computational burden and comparative longer execution time than MRAS and RLS. It is difficult to design the algorithm for multi parameter measurement.

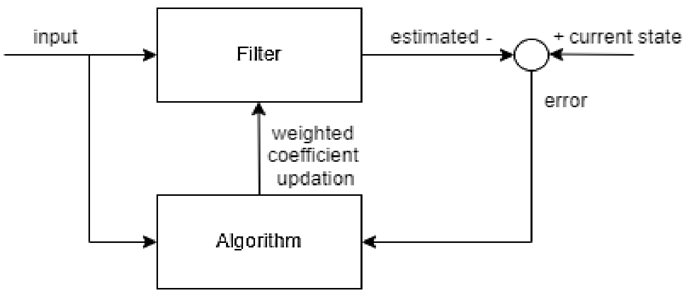

Figure 4. RLS algorithm

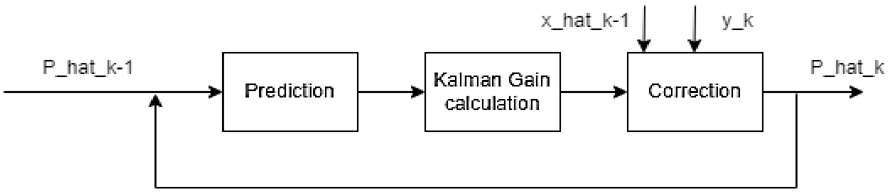

Figure 5. EKF Algorithm

The main drawback of EKF is that it has large sampling time. This is overcome by DKF method. The results of Jacobian matrix for DKF is identity matrix. This algorithm is least noisy and has accurate mean value under load step condition. Computational load can be reduced using this method. The idea behind model reference adaptive system is that it makes error calculation from reference model and a adjustable model as shown in Figure 6 using adaptive mechanism error is minimized. Adaptive mechanism includes Popov stability criteria and Lyapunov stability theorem. MRAS has good results and less implementation complexity [29]. MRAS possesses advantage of less execution time than EKF. This method is sensitive to noise, and it is difficult to be used in multi parameter identification of missing rank. It increases the difficulty of identification algorithm [29]. The gain matrix of recursive prediction error method can be identified using different algorithm like Gauss Newton method (GNA) and the stochastic gradient algorithm (SGA). According to Perera [44], in low-speed region GNA has rapid adaptation of flux linkages than SGA. Simultaneous adaptation without zonal scheduling scheme is possible with GNA [47]. This method is more effective when steady state solution used for flux linkage and dynamic part for R_s. To define system characteristics fractional mathematical models are more accurate than integer order models because essence of capacitance, inductance are fractional order. Li [51] used Levenberg-Marquardt algorithm (LM) with variable damping factor to identify fractional order model parameters with steps. Akpunar [39] proposed extended state observer predictive speed control algorithm for PMSM drives and implemented using Runge-Kutta method. Runge-Kutta method has simplicity of modelling and better constraint handling capability. It is robust but it has computational burden. Rengifo [46] represented instantaneous input impedance model along with disturbance discrete model considering features such as harmonics, saturation. Values of parameters according to interior points and genetic algorithm are given. Interior points algorithm requires less computing time. For multiparameter coupling problems, an improved PSO algorithm based on Gaussian decline and Gaussian disturbance can be used [34]. In, a metaheuristic algorithm for a continuous time system using a photovoltaic model is implemented [35] and compared to PSO in [38]. To estimate Li-ion battery parameters with high convergence speed and low complexity, artificial ecosystem-based optimization is used [36]. In the future, a metaheuristic algorithm for PMSM parameter estimation could be investigated.

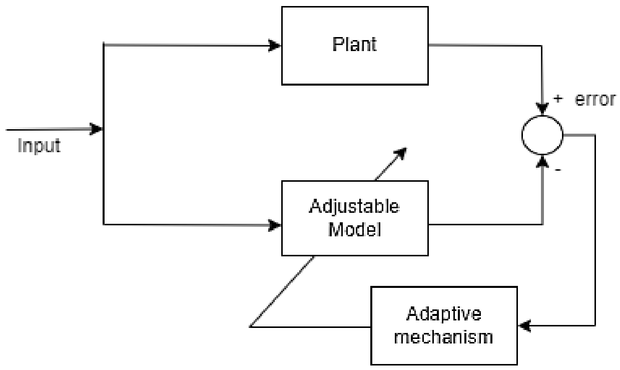

Figure 6. MRAS algorithm

4. DISCUSSION

Table 1 gives comparative analysis between different methods in terms of convergence speed, computational complexity, initial value requirement and sensitivity to noise. RLS and RPEM have fast convergence speed compared to others. EKF has property to reject measurement and process noise, but EKF have more computational complexity compared to RPEM. Depending upon method used the criteria for initial value requirement changes. Some methods require initial parameter value so that convergence time get reduced. Noise sensitivity is an important factor which affects the accuracy of algorithm. Kalman filter have advantage of considering noise while estimating the parameters.

Table 1. Comparative study of methods

Features	Methods					
	RLS	EKF	MRAS	HF Injection	RPEM	Fractional order-based LM
Convergence speed	Faster	Slower	Slower	-	Fastest	Fast
Computational Complexity	Less	More	Less	-	Substantial	-
Initial value requirement	-	Required	-	-	Required	Required
Sensitive to noise	More	Immune	Less	More	-	-

Table 2 gives brief about percentage of identification error for parameters considering the method and different effects. Operating conditions of motor such as temperature, magnetic saturation affects stator resistance and inductances. R_s, L_d, L_q vary with rotor position and frequency. In EV application the inverter non-linearities also need to be considered while controlling the performance for efficiency. Table 2 provides the identification error percentage for parameter estimation using different methods under various consideration such as VSI non-linearities, temperature, saturation, or no consideration. The identification error can be calculated as:

$$Identification\ error = \frac{|identification - true|}{true} * 100\%$$

Here, identification and true means the estimated or identified and the true value of the parameter respectively. Identification error is the error in estimating the parameter value and the actual value.

One can use Table 1 results to decide the method for parameter identification depending upon the features one wants for estimation. Along with it Table 2 gives scope for method finalization in terms of identification error of method either without any consideration or with considering effects such as temperature and VSI non- linearities.

Table 2. Identification error considering various effects

Method or Effect	Without any consideration				Temperature effect				VSI Non-Linearities				Add-ons or reference
	R_s	L_d	L_q	Ψ_f	R_s	L_d	L_q	Ψ_f	R_s	L_d	L_q	Ψ_f	
RLS	4.61	1.87	2.45	-2.5	-	-	-	-	-	-	-	-	[21]
	-	-	-	-	-2.3	-0.06	0.19	0.02	-	-	-	-	[49]
	-	-	-	-	0.5	0.36	0.86	-	-	-	-	-	MTPA Control [4]
MRAS	-	-	-	-	0.003	0.0004	0.0004	0.0004	-	-	-	-	(10^{-6}), Improved adaptive law [29]
	-	-	-	-	-	-	-	-	4	-	-	-	[29]
EKF	-	-	-	-	1.8	0.24	0.24	-	-	-	-	-	Gradient correction [31]
	-	-	-	-	-	-	-	-	-2.3	-0.3	-0.3	-1.5	[32]
HF Injection	-	-	-	-	-	-	-	-	5	5	6	9.5	[41]
RPEM	-	-	-	-	-	-	-	-		-	-	10	SGA [40]

5. CONCLUSION

This paper represents an overview on different numerical methods that are available for online parameter estimation considering that the position sensor is present in the system. The basic idea of methods with their advantages and disadvantages are provided. It also gives identification error percentage values for numerical methods with consideration of various effects. The comparison between methods in terms of convergence speed, computational complexity, sensitivity to noise and initial value requirement is also provided. Selection of the numerical method for parameter identification of PMSM is possible using this literature depending upon the user's constraint for method selection such as convergence speed, identification error range, and computational time. Further scope is to implement any of the method to get accurate parameters of motor.

Having fast convergence speed, RLS is the most used method for motor parameter estimation but it does not consider the noise effect. Having noise consideration by default and if temperature and saturation effects are to be considered, EKF is the useful method for parameter estimation but the computational complexity is more. As a future scope one can use EKF for L_d, L_q estimation and RLS for R_s and flux linkage estimation of PMSM, as EKF has more computational burden.

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