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Estimation performance of the novel hybrid estimator based on machine learning and extended Kalman filter proposed for speed-sensorless direct torque control of brushless direct current motor

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ABSTRACT

In this study, machine learning (ML) based methods are used to estimate rotor mechanical speed of brushless direct current (BLDC) motors. Training performances of approaches such as Artificial Neural Network, k-Nearest Neighbor, and Random Forest in the ML-based speed estimator are tested using the datas obtained from the direct torque control (DTC) drive system of BLDC motor in simulation and it is seen that the ANN approach has the highest accuracy. In addition, a novel extended Kalman filter (EKF)-based estimator is proposed for the estimation of back-EMFs of BLDC motor. A hybrid estimation method is proposed by using the developed ML-based speed estimator with the proposed EKF-based estimator and its estimation performance is tested in simulation on DTC drive system.

1. Introduction

The term "Artificial Intelligence (AI)" was initially coined by John McCarthy during the seminal Dartmouth conference in 1956, held in the United States. This conference, convened by prominent figures in the field of AI and information processing theory, such as Marvin Minsky and Claude Shannon, marked a significant milestone in the formal establishment of the AI discipline (Shapiro,1992; Nilsson, 1998; Brooks, 1991; Ghahramani, 2015; Winston, 1984). However, it is noteworthy that the concept of AI has been contemplated long before that period. As early as 1950, Alan Turing put forth the notion of a "thinking machine," proposing the feasibility and introducing the Turing test as a benchmark for gauging machine intelligence (Turing, 1950).

Machine learning (ML) represents a facet of AI wherein the investigation and implementation of algorithms enable the extraction of novel insights from pre-existing datasets. This domain of study exhibits considerable affinity with computational statistics, as both disciplines share the common objective of making predictions through computational means (Zhou, 2021; Ghahramani, 2015). Moreover, ML closely intertwines with mathematical optimization, which plays a fundamental role in the development of methodologies, theoretical underpinnings, and application frameworks within this field. Notwithstanding, it is worth noting that ML is occasionally misconstrued with data mining (Mannila, 1996; Mahesh, 2020).

The field of ML which is an AI-based structure has seen significant growth and advancement in recent years. ML is a set of software and hardware systems that behave like human beings by imitating human intelligence by developing themselves in line with experiences gained and transforming them into action (Russell and Norvig, 2016; Jiang et al., 2017). ML is used to analyze complex data in different fields and to make it more understandable (Lu et al., 2018; Hosny et al., 2018). ML is used in many different fields such as education (Wang and Tao, 2018), medicine (Topol, 2019), automotive (Luckow et al., 2018), cyber security (Süzen, 2020), and financial services (Wall, 2018). One area where ML can be particularly useful is in the speed estimation of brushless direct current (BLDC) motors (Purushothaman and Santha, 2022).

The development of AI-based motor systems has effectively made use of ML algorithms like k-Nearest Neighbor (k-NN) (Casimir et al., 2006), Support Vector Machines (SVM) (Liu et al., 2018; Martínez-Morales et al., 2018), Artificial Neural Networks (ANN) (Han et al., 2006; Su and Chong, 2007; Sun et al., 2016), Bayesian Classifier (BC) (Baraldi et al., 2015), Decision Trees (DT) (Li et al., 2018), Random Forest (RF) (Quiroz et al., 2018), and Seep Learning (DL) (Janssens et al., 2016). Recently, DL and ML have been used for recognition systems by motor researchers (Lei et al., 2016; Cheon et al., 2015; Hausmann et al., 2021; Caramiaux et al., 2020; Elsrogy et al., 2013).

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BLDC motors are commonly used in many industrial and consumer applications, including electric vehicles, drones, robotics, and more (Xuan Ba et al., 2018). BLDC motors have star or delta connected coils in their stator and permanent magnets in their rotor. The commutation of BLDC motor is provided electronically by semiconductor switchings. Rotor position information is needed to instantly determine the phase pair to be commutated during the commutation. Rotor position information is determined by position sensors. In a BLDC motor, rotor position information can be measured with hall sensors placed on the stator windings with a phase difference of 120 or 60 electrical degrees. Thus, the switching states of the inverter driving the BLDC motor are determined by the value of these hall sensors in the binary system (Krishna Veni et al., 2022).

In control methods in which the position sensors are used, they have disadvantages such as difficulty in positioning the sensor on the motor shaft or stator windings, wiring complexity, high cost and reliability. For these reasons, sensorless control methods are proposed in the literature. Although sensorless control methods have many advantages, they have heavy computation burden and require complex algorithms (Çabuk, 2021; Adil et al., 2016; Mohanraj et al., 2022).

Recently, ML can be used to develop more cost-effective and efficient methods of speed estimation for BLDC motors. The process involves training a model on a large dataset of motor speed, current and voltage measurements. The model learns to identify patterns in the data and can then use this knowledge to estimate the motor speed in real-time (Unlersen et al., 2022).

Also the knowledge exact value of the back EMF of the BLDC motor is an other important state in order to ensure the dynamic control of the BLDC motor like direct torque control (DTC), field oriented control, sliding mode control, model predictive control etc. The precise knowledge of the non-sinusoidal back-EMF of the BLDC motor is important for the observation of the motor flux. Recently, various studies are proposed to determine the back-EMF (Purushothaman and Santha, 2022; Selva Pradeep and Marsaline Beno, 2022).

The studies proposed in the literature for the determination and estimation of the back-EMF of the BLDC motor are examined in detail in Mazaheri and Radan (2017), Çabuk (2021), Gamazo-Real et al. (2010), and Gamazo-Real et al. (2022). The popular method about the determinatıın of the back-EMF of BLDC motor are classified as direct measurement and indirect method. While the back-EMF zero-crossing floating detector and third harmonic voltage measurement which have limited accuracy at low speeds and need open-loop starting strategy and auxiliary filters are included in the direct measurement methods, on the other hand the model-based estimator like sliding mode observer, AI, and the extendend Kalman filter (EKF) are defined as indirect method and these are preferred in the literature due to the aforementioned disadvantages of direct measruement methods. Among the existing methods in the literature, EKFs are widely preferred due to their high estimation performance depending on the stochastic structure (Mazaheri and Radan, 2017). The fact that it has a simpler and more stable structure compared to other methods which have heavy computational burden and based on deterministic model also causes the EKF to get ahead of other methods.

Rotor position and rotor speed information required for the sensorless control of the BLDC motor can be obtained from the estimated back-EMF values of the BLDC motor with EKF. However, the difficulty in estimating the back-EMF at low speeds and zero speeds may affect the accuracy of the knowledge of rotor position and speed information (Hooshmand et al., 2023). For this reason, hybrid estimation methods can be recommended both to increase the estimation performance by reducing the degree of the EKF structure and to obtain rotor speed and position information in a more stable manner.

At this point, the use of ML for speed estimation has several advantages over traditional methods. For example, it can be implemented using low-cost sensors, such as current sensors and voltage sensors, which are already present in many motor control systems. It also provides more accurate speed estimation, even in situations where the motor speed changes rapidly in a wide speed range from zero to rated speed under variable load conditions. Overall, the use of ML for speed estimation of BLDC motors has great potential for improving the efficiency and performance of various industrial and consumer applications. In the literature, ML-based speed estimator structures created with different training methods are proposed. In Yao et al. (2023), a rotor speed and rotor position estimator is proposed in which the training architecture is based on multi-layer perceptron topology neural networks and in the related work, stator voltages, currents and rotor speed are used for training and the estimation performance is tested while the BLDC motor is operating under no-load conditions. In Celikel (2019), in order to reduce the position measurement error, an Fied Programmable Gate Array (FPGA)-based ANN structure is developed and speed and position of BLDC motor obtained as two outputs from the proposed ANN. The proposed ANN has 3 inputs, 10 neurons in hidden layer and 2 outputs, and its training is implemented on an FPGA and its estimation performance is tested on FPGA in hardware in the loop simulation. Also in Gamazo-Real et al. (2022), rotor speed and position are estimated by using two-three layer ANNs with perceptron-based cascade topology and it is understood from the results and discussion of the authors that the speed estimation error increases while the BLDC motor is running at rated speed under full-load condition. In order to improve the achievement of ANN on the motor control and parameter or state estimations, it is applied with various topologies (Batzel and Lee, 2003; Guo et al., 2008; Monmasson et al., 2011; Zine et al., 2018). The authors in Batzel and Lee (2003) offer a diagonally recurrent ANNs in order to improve the convergence. Double ANN models are used and correlated each other in Guo et al. (2008) in order to estimate the phase current and back-EMF of BLDC motor. In addition to the studies that are carried out to improve the training methods of ANN, FPGA-based studies are also carried out with the aim of reducing the algorithm computational burden of ANN algorithms and thus increasing the training speed and convergence achievement as proposed in Celikel (2019) and Monmasson et al. (2011). But all of these proposed FPGA-based methods need expertise and FPGAs have limited area to implement the ANN algorithms. In addition, due to the serial processing capacity of DSP-based evolution platforms, the computational burden and complexity of ANNs poses a major problem, especially in real-time applications. As mentioned in Putra et al. (2022), ANN-based ML which is a subsequent of AI gains importance on motor control and parameter or state estimations due to its advantages on the capability to recognize and learn the nonlinear systems. In Zine et al. (2018), it is aimed to ensure the real-time deployment, a feed-forward ANNs are trained with Levenberg-Marquardt method which has a simplified network topology. For the estimation of the rotor position of a permananet magnet synchronous motor, a ML-based observer which is trained by using a modified Elman neural network is proposed in Putra et al. (2022), and the proposed ML-based estimator is trained offline by using the datas obtained from field oriented control (FOC) implemented in simulation. As a result, when the studies in the literature are examined, there is no study comparing the performance of different algorithms proposed for training ML and AI-based methods which are designed in order to estimation of rotor speed or any other state/parameter of BLDC motor.

The main contribution of this study is to propose a hybrid estimator structure in order to estimate the three-phase back-EMFs and rotor mechanical speed of BLDC motor. For this purpose a novel EKF-based and ML-based estimators for back-EMFs and rotor speed of BLDC motor, respectively. During the development of the hybrid estimator, different algorithms existed in the literature are used to train the ML-based estimator. Non-sinusoidal three-phase back-EMFs should be known especially in the determination of the amplitude and position information of the motor flux, and also the rotor mechanical speed which calculation from the back-EMF information of BLDC motor is difficult at low speed should be estimated in order to ensure the dynamic control of BLDC motor which robust dynamic control is gained importance in various industrial applications. The other reason for suggesting a hybrid estimator method in this study is that the increase in the number of estimated states and parameters in the EKF, where the measurement matrix and estimation stability are directly related, increases the order of the nonlinear dynamic model applied as a function of the inputs to the EKF and negatively affects the estimation stability and implementation of the EKF algorithm in discrete time. For this purpose, a new EKF-based estimator, in which 3-phase stator currents and 3-phase back-EMFs are estimated, and a ML-based speed estimator structure are proposed and thus a novel hybrid estimator method is implemented with these two different estimator methods. In this hybrid estimator method, the 3-phase stator currents and 3-phase stator back-EMFs are estimated by EKF and applied to the ML-based speed estimator and the rotor mechanical speed is estimated. Thus, both the number of predicted parameters and states are increased and a stable estimation structure is revealed.

In this study, a speed-sensorless DTC drive system is implemented in simulation to test the estimation performance of the proposed hybrid estimator. Before the simulation tests, in order to train the ML-based speed estimator resulting in a numerical prediction model for speed estimation of the BLDC motor, 3-phase stator currents and 3-phase back-EMFs obtained in the simulation environment are used as training datas and speed information is used as target datas. By using different training algorithms, the accuracy performance of these algorithms with respect to each other is compared. At the end of the training, it is proved that the ML-based rotor speed prediction model achieves an impressive accuracy of 99.85% in speed estimation.

The estimation performance of the proposed hybrid estimation method, which is generated as a result of the development of the novel EKF-based estimator and the training of the ML-based speed estimator, is tested in a simulation on a speed-sensorless DTC drive system. As a result of the tests carried out in a wide speed range under different load torques, it is seen that the proposed hybrid estimator has high estimation accuracy and thus high performance dynamic control of the BLDC motor can be achieved.

2. Materials and methods

The materials and methods section of the study initially describes the discretized model of the BLDC motor, followed by details about the dataset utilized for training ML algorithms. Additionally, basic information regarding the ANN, RF, and k-NN algorithms employed in training the dataset is provided.

In the methodology section, the numerical estimation of the three-phase stator currents and three-phase back-EMFs for the BLDC motor is performed using the EKF. Subsequently, the ML algorithms (ANN, RF, and k-NN) are applied to the numerically obtained three-phase stator current and three-phase back-EMF dataset from the EKF in the second part of the method section.

2.1. Materials

2.1.1. Discretized model of BLDC motor

Outer rotor BLDC motors are widely preferred in unmanned aerial and land vehicles as well as hybrid and pure electric vehicles due to their high efficiency. The 3-phase stator currents and motion equations of outer rotor BLDC motor model are given as the following discretized form:

$$i_{sa}(k+1)=\left(-\frac{R_s}{L_{ls}}T+1\right)i_{sa}(k)+\left(\frac{v_{sa}(k)-e_a(k)}{L_{ls}}\right)T \tag{1a}$$

$$i_{sb}(k+1)=\left(-\frac{R_s}{L_{ls}}T+1\right)i_{sb}(k)+\left(\frac{v_{sb}(k)-e_b(k)}{L_{ls}}\right)T \tag{1b}$$

$$i_{sc}(k+1)=\left(-\frac{R_s}{L_{ls}}T+1\right)i_{sc}(k)+\left(\frac{v_{sc}(k)-e_c(k)}{L_{ls}}\right)T \tag{1c}$$

$$\omega_m(k+1)=\left(\frac{\varphi_{ra}(k)i_{sa}(k)+\varphi_{rb}(k)i_{sb}(k)+\varphi_{rc}(k)i_{sc}(k)}{J_l}\right)-\frac{B_L\omega_m(k)T}{J_l}-\frac{\tau_l T}{J_l}+\omega_m(k) \tag{2}$$

$$\tau_{ind}=\varphi_{ra}(k)i_{sa}(k)+\varphi_{rb}(k)i_{sb}(k)+\varphi_{rc}(k)i_{sc}(k) \tag{3}$$

where, i_{sa}, i_{sb}, and i_{sc} are the 3-phase stator currents of BLDC motor. v_{sa}, v_{sb}, and v_{sc} are 3-phase stator voltages of BLDC motor. e_a, e_b, and e_c are back-EMF values of BLDC motor. R_s and L_{ls} are stator resistance and stator leakage inductance of BLDC motor, respectively. ω_m is the rotor mechanical angular speed of BLDC motor. τ_l and τ_{ind} are load torque and induced torque of BLDC motor, respectively. φ_{ra}, φ_{rb}, and φ_{rc} are rotor 3-phase leakage flux values of BLDC motor. J_l and B_l are total moment inertia (includes the inertia of motor shaft and mechanical load) and total viscous friction (represents the coefficient of the shaft viscous and ventilation loss) of BLDC motor. T is the sampling time of the discrete-time system.

The mathematical expressions of 3-phase components of back-EMF and rotor flux of BLDC motor model which have trapezoidal wave forms are given as the following form in discrete-time with the electrical rotor position of BLDC motor (Θ_e):

$$\theta_e(k+1)=p_p\omega_m(k+1)+\theta_e(k) \tag{4}$$

$$\varphi_{ra}(k)=\left(\cos\left(\theta_e(k)\right)\right)_{-lim_{trap}}^{lim_{trap}}\frac{\left|\overrightarrow{\varphi}_r\right|}{\lim_{trap}} \tag{5a}$$

$$\varphi_{rb}(k)=\left(cos\left(\theta_e(k)-2\pi/3\right)\right)_{-lim_{trap}}^{lim_{trap}}\frac{\left|\overrightarrow{\varphi}_r\right|}{lim_{trap}} \tag{5b}$$

$$\varphi_{rc}(k)=\left(cos\left(\theta_e(k)+2\pi/3\right)\right)_{-lim_{trap}}^{lim_{trap}}\frac{\left|\overrightarrow{\varphi}_r\right|}{lim_{trap}} \tag{5c}$$

$$e_a(k)=p_p\omega_m(k)\varphi_{ra}(k) \tag{6a}$$

$$e_b(k)=p_p\omega_m(k)\varphi_{rb}(k) \tag{6b}$$

$$e_c(k)=p_p\omega_m(k)\varphi_{rc}(k) \tag{6c}$$

here, p_p is the pole pair of BLDC motor. $\left|\overrightarrow{\varphi}_r\right|$ is the magnitude of the rotor flux vector of BLDC motor.

Moreover the trapezoidal wave form of 3-phase components of the back EMF and rotor flux of the BLDC motor model are provided by limiting and cutting the sinusoidal wave form with trapezoidal wave treshold lim_{trap}.

In this study, which is proposed for the speed-sensorless novel

Table 1
BLDC motor parameters.

DC power supply	V	72
Rated speed	rpm	750
Rated torque	$N.m$	21
Rated power	kW	1.5
Moment of inertia	$kg.m^2$	0.0073
Phase back-EMF coefficient	$V_{peak}/krpm$	96
Phase resistance	Ω	0.033
Leakage inductance	mH	0.1594
Mutual inductance	mH	0.0254727
Pole pairs		23

extended Kalman filter and ML-based DTC of the BLDC motor, the parameters given in Table I are used in the BLDC motor model.

2.1.2. Dataset

In this study ML-based speed estimator proposed for the estimations of i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c states/parameters of BLDC motor. Table 2 presents the statistical informations of the dataset obtained from a simulation environment, which were collected for the purpose of developing a ML-based speed estimation system.

Table 2 shows the statistical information of the dataset utilized for estimating the speed of the BLDC motor. The study employed 2.8 million samples. For each feature in the dataset, the mean, standard deviation, minimum, and maximum values were analyzed. Fig. 1 presents the correlation matrix of the dataset collected within the simulation environment. Upon inspecting the correlation matrix, it can be observed that the correlation values between the parameters isa, i_{sa}, i_{sb}, i_{sc}, e_a, e_b, e_c, and ω_m are relatively small, ranging from −0.0014 to 0.09. These low correlation values indicate that the dataset does not exhibit a strong linear relationship between these parameters and ω_m.

2.1.3. Artificial Neural Networks

ANNs are formed by imitating the biological neural structure of the human brain on computers. ANN uses previously memorized or classified information with the help of neural sensors. Thus, they are computer programs used in the formation of new information and decision-making (Efe et al., 1999; Narendra and Parthasarathy, 1990).

ANN is used in different real-life areas such as the automotive industry (track tracking, guidance), banking (signature recognition), aerospace industry (flight simulations), electricity (chip deterioration analysis), finance (exchange rate forecasts), healthcare (early diagnosis and treatment of cancer), military (determination of flight directions in military airplanes), industry (design of products) (Abiodun et al., 2018).

In general, ANN consists of three type of layers. These layers are the input, hidden, and output layers. In the first layer, the input layer, the dataset coming from outside is accepted by the ANN. The layer between these two layers, which may be one or more, is called the hidden layer (Karakaya, 2007). The hidden layer in ANN plays a crucial role in learning and capturing complex patterns and features within the input datas. It transforms raw data into a higher-level representation, using weighted sums and activation functions, enabling the network to model non-linear relationships. The hidden layer's purpose is to extract relevant and abstract features, which are then used for making predictions or decisions in the output layer. Through backpropagation, the network adapts its internal weights during training to minimize prediction errors and improve its performance on various ML tasks.

As seen in Fig. 2, the dendrites (input signals) of the artificial neuron are expressed as x_n, and the weight coefficient (significance degree) of each dendrite as wn. The kernel, which is expressed as a sum function, shows the weighted sums (F(Σ)) of all input signals. This sum signal is directed to the synapse (weights) as an input to the activation function. The resulting signal from this function is denoted as y and is directed to be fed to the other cell (Köktürk, 2009).

ANNs demonstrate remarkable versatility, finding application across an extensive array of tasks, such as object recognition, image classification, segmentation, facial recognition, natural language processing (NLP), speech recognition, recommendation systems, financial analysis, medical image analysis, disease diagnosis, patient risk stratification, and personalized treatment plans. Their flexibility and adaptability have led to their widespread adoption in diverse fields, showcasing their profound impact on advancing the frontiers of AI.

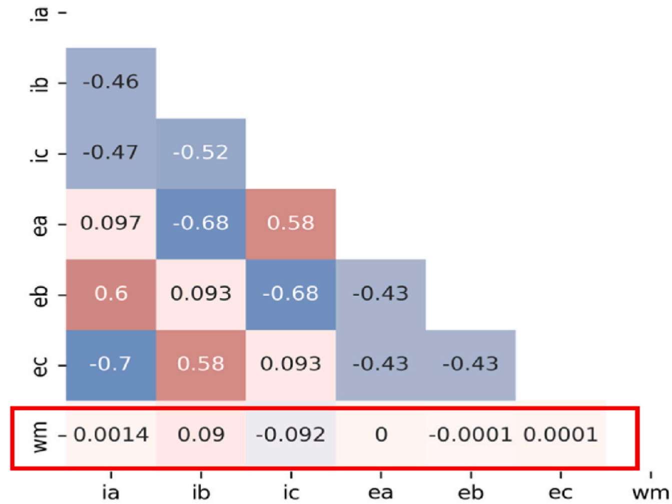

Fig. 1. Correlation matrix of BLDC motor dataset.

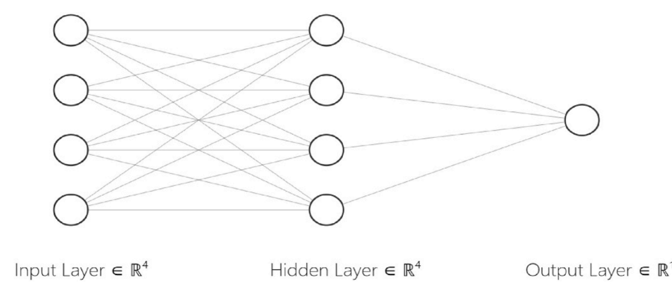

Fig. 2. ANN structure.

The selection of ANNs is driven by a multitude of reasons. Firstly, ANNs possess the remarkable capability to model complex and nonlinear relationships within data, enabling them to tackle intricate real-world problems effectively. Secondly, their ability to learn from large-scale datasets and extract high-level abstractions makes them well-suited for tasks involving vast amounts of information (Basheer and Hajmeer, 2000; Abiodun et al., 2018; Olden and Jackson, 2002).

2.1.4. Random forest

RF is a popular ML algorithm that belongs to the ensemble family of methods. It is used for both classification and regression tasks and is considered one of the most powerful algorithms in ML due to its ability to produce accurate and reliable predictions (Kavzoglu and Teke, 2022).

The RF algorithm builds a large number of decision trees and then aggregates their results to make a final prediction. Each decision tree is built using a random subset of the training data and a random subset of the features (Xu et al., 2022). By combining the predictions of many such trees, random forest is able to reduce overfitting and produce more robust and accurate predictions (Park et al., 2022).

RF has a wide range of applications in areas such as finance (Zhu,

Table 2
BLDC motor dataset statistical informations.

Feauture	i_{sa}	i_{sb}	i_{sb}	e_a	e_a	e_c	speed
Mean	−0.058	−3.982	4.039	0.0009	0.0003	−0.0011	490.17
Std	71.938	74.564	74.587	24.217	24.217	24.217	291.864
Min	−154.255	−149.934	−152.447	−36.551	−36.575	−36.568	−18.455
Max	152.038	153.747	155.475	36.569	36.568	36.575	761.934

2022; Zhang et al., 2022), medicine (Doubleday et al., 2022; Dinesh and Kalyanasundaram, 2022) and engineering (Sun et al., 2023; Salem et al., 2022). It is particularly useful when dealing with high-dimensional feature spaces and large datasets. RF is also an interpretable model, allowing users to understand how it arrived at a particular prediction.

The selection of the RF algorithm is underpinned by several compelling considerations. Firstly, its robustness against overfitting and commendable performance on complex datasets render it an attractive choice. Additionally, the algorithm's ability to furnish measures of feature importance contributes to effective feature selection strategies. Furthermore, RF exhibits reduced sensitivity to outliers in comparison to individual decision trees, bolstering its suitability for diverse and challenging data scenarios (Breiman, 2001; Díaz-Uriart & Alvarez de Andrés, 2006).

2.1.5. K-nearest neighbors

k-NN is a ML algorithm used for classification and regression tasks. It is a non-parametric algorithm, which means it makes no assumptions about the underlying data distribution (Sharifi, 2021; Vapnik et al., 1997). The k-NN algorithm works by calculating the distance between a new input data point and all the existing data points in the training set. The distance is typically calculated using a distance metric, such as Euclidean distance or Manhattan distance.

The 'k' closest data points to the new input point are then selected based on the distance metric and are used to determine the class or regression value of the new input point (Dissanayake et al., 2022). The choice of 'k' is a critical hyperparameter in the k-NN algorithm. A small 'k' value can result in overfitting, while a large 'k' value can lead to underfitting. The distance metric used is also important, as it can affect the performance of the algorithm (Benarafa et al., 2023).

The rationale behind opting for the algorithm encompasses several salient factors. Firstly, its selection is motivated by its simplicity and ease of implementation, making it accessible for practical applications. Moreover, the non-parametric nature of k-NN facilitates its adaptability across diverse data types, accommodating a wide array of problem domains. Notably, k-NN's efficacy is particularly pronounced in scenarios characterized by intricate decision boundaries, where data points are intricately intertwined and not readily separable (Wu et al., 2008; Bhuvaneswari and Therese, 2015).

2.2. Methods

The method part of the study consists of two stages: EKF for back-EMF estimation and ML modeling for speed estimation.

2.2.1. Extended Kalman filter for Back-EMF estimation of BLDC motor

In this study a novel EKF-based estimator is proposed for e_a, e_b, and e_c estimations of the BLDC motor with i_{sa}, i_{sb}, and i_{sc}. During the estimation process of the proposed EKF-based estimator 3-phase stator currents and 3-phase stator voltages are measured and applied to the EKF algorithm as measurement vector and control input vector, respectively. Also, n_m is estimated with a new ML-based estimator and the estimated value of n_m is used in order to observe the 3-phase components of rotor and stator fluxes from the estimated 3-phase back-EMF and 3-phase stator current values. The observed 3-phase stator flux components are used to determine the sector and magnitude on the vector space of the motor flux for DTC of the BLDC motor. Also the induced torque is obtained by taking into account the observed 3-phase rotor flux components and ω_m which is fed back from the artificial intellegence-based estimator.

The extended model of the BLDC motor which is used for the estimation of i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c states/parameters with a novel EKF-based estimator is given the following discretized general form:

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)) + \mathbf{w} = \mathbf{A}(\mathbf{x}(k))\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{w} \tag{7}$$

$$\mathbf{Z}(k) = \mathbf{H}\mathbf{x}(k) + \mathbf{v} \text{ (Measurement Equation)} \tag{8}$$

where $\mathbf{x}$ is the extended state vector; $\mathbf{f}$ is the nonlinear function of the states and parameters; $\mathbf{A}$ is the system matrix; $\mathbf{B}$ is the input matrix; $\mathbf{U}$ is the control input vector; $\mathbf{Z}$ is the measurement matrix; $\mathbf{Z}$ is the output vector; $\mathbf{w}$ and $\mathbf{v}$ are system and measurement noise matrix, respectively and they are diagonal white Gaussian noise matrices.

The matrices and vectors of the extended model of BLDC motor which is used in the EKF algorithm are represented in (9) and (10). In the proposed EKF-based estimator, i_{sa}, i_{sb}, and i_{sc} are defined as states while e_a, e_b, and e_c are defined as parameters to be estimated.

$$\underbrace{\begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \\ e_a \\ e_b \\ e_c \end{bmatrix}}_{\mathbf{x}(k+1)} = \underbrace{\begin{bmatrix} -\frac{R_s}{L_{ls}}T+1 & 0 & 0 & -\frac{T}{L_{ls}} & 0 & 0 \\ 0 & -\frac{R_s}{L_{ls}}T+1 & 0 & 0 & -\frac{T}{L_{ls}} & 0 \\ 0 & 0 & -\frac{R_s}{L_{ls}}T+1 & 0 & 0 & -\frac{T}{L_{ls}} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\mathbf{A}(\mathbf{x}(k))} \underbrace{\begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \\ e_a \\ e_b \\ e_c \end{bmatrix}}_{\mathbf{x}(k)} + \underbrace{\begin{bmatrix} \frac{T}{L_{ls}} & 0 & 0 \\ 0 & \frac{T}{L_{ls}} & 0 \\ 0 & 0 & \frac{T}{L_{ls}} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} v_{sa} \\ v_{sb} \\ v_{sc} \end{bmatrix}}_{\mathbf{u}(k)} + \mathbf{w} \tag{9}$$

$$\underbrace{\begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \end{bmatrix}}_{\mathbf{Z}(k)} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}}_{\mathbf{H}} \underbrace{\begin{bmatrix} i_{sa} \\ i_{sb} \\ i_{sc} \\ e_a \\ e_b \\ e_c \end{bmatrix}}_{\mathbf{x}(k)} + \mathbf{v} \tag{10}$$

In this study convensional EKF-based estimator which nonlinear function consists of a novel BLDC model is used the estimation of i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c states/parameters in order to improve the DTC of BLDC motor with the proposed ML-based speed estimator. The general equation of the convensional EKF algorithm can be given as the follows (Zerdali, 2020):

1. Initialization:

$$\hat{\mathbf{x}}(0) = E[\mathbf{x}(0)] \tag{11}$$

$$\mathbf{P}(0) = E\left[(\mathbf{x}(0) - E[\mathbf{x}(0)])(\mathbf{x}(0) - E[\mathbf{x}(0)])^T\right] \tag{12}$$

2. Linearization:

$$\mathbf{F}(k+1,k) = \frac{\partial \mathbf{f}(\mathbf{x}(k),\mathbf{u}(k))}{\partial \mathbf{x}(k)}\bigg|_{\hat{\mathbf{x}}(k)} \tag{13}$$

3. Time update:

$$\mathbf{x}(k)^- = \mathbf{f}(\hat{\mathbf{x}}(k-1),\mathbf{u}(k)) \tag{14}$$

$$\mathbf{P}(k)^- = \mathbf{F}(k,k-1)\mathbf{P}(k-1)\mathbf{F}^T(k,k-1) + \mathbf{Q} \tag{15}$$

4. Measurement update

$$\mathbf{K}(k) = \mathbf{P}(k)^-\mathbf{H}^T\left[\mathbf{H}\mathbf{P}(k)^-\mathbf{H}^T + \mathbf{R}\right] \tag{16}$$

$$\hat{\mathbf{x}}(k) = \hat{\mathbf{x}}(k)^- + \mathbf{K}(k)(\mathbf{Z}(k) - \mathbf{H})\hat{\mathbf{x}}(k)^- \tag{17}$$

$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H})\mathbf{P}(k)^- \tag{18}$$

where, **I** is the identity matrix; $\mathbf{P}(k)^-$ and $\mathbf{P}(k)$ are priori and posteriori estimation error matrices, respectively; $\mathbf{F}(k)$ is the extended function of states and parameters obtained by linearized the nonlinear function of states and parameters with Taylor series; $\mathbf{K}(k)$ is the Kalman gain; **Q** is the covariance matrix of system noise or modelling erros; **R** is the covarince matrix of measurement noise or output errors. Furthermore **w** in the generalized model corresponds to **Q** in the EKF algorithm, and **v** corresponds to **R**.

2.2.2. Modeling speed of BLDC motor by machine learning

In the study, the work flow diagram given in Fig. 3 is used for the training of the data set created for the BLDC engine with ML algorithms. Firstly, a dataset of 2.8 million samples is collected by collecting the i_{sa}, i_{sb}, i_{sc}, e_a, e_b, e_c and n_m states/parameters of the BLDC motor. This dataset is divided into two as test and train. In the next stage, the dataset is trained with ANN, RF and k-NN algorithms. The trained models are evaluated with Coffiecent of Determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and response time (predicatin time) evaluation criteria and the most suitable model is used in the simulation environment.

The strategy employed for training ANNs involved a systematic exploration of parameter configurations aimed at aligning the neural network with the characteristics of the dataset. This is achieved by utilizing the grid search optimization algorithm. The training strategy centered on refining the neural network's performance to attain the lowest achievable loss. Key hyperparameters subjected to tuning encompassed the quantity of hidden layers, the neuron count within each hidden layer, and the learning rate.

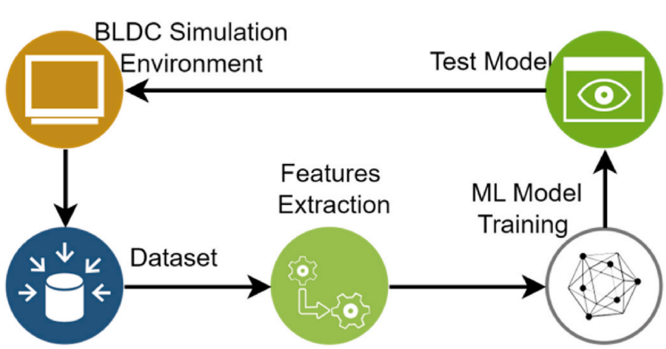

Fig. 3. ML modeling for BLDC motor speed estimation.

Table 3
Evaluation of hyperparameters of ML algorithms by using GridsearchCV.

Algorithm	Hyperparameters	Values	Best value
k-NN	K	linspace (10,200,20)	80
RF	number of trees	linspace(1, 51,11)	26
	maximum depth	linspace(0,2,5)	1.5
	minimum number of samples	linspace(1,6,11)	2
ANN	number of neurons for each layer	linspace(1,10,10)	8,5
	number of layers	linspace(1,3,3)	2
	Learning rate	linspace (0.01,0.1,10)	0.05

Hyperparameter tuning is a critical step in optimizing the performance of ML algorithms. Grid search, a popular method for hyperparameter tuning, systematically explores a predefined set of hyperparameter values to identify the combination that yields the best performance. For ANNs, the number of hidden layers, the number of neurons in each layer, and the learning rate hyperparameters are tuned. In the case of k-NN, the primary hyperparameter 'k' representing the number of nearest neighbors, was tuned. For RF, hyperparameters such as the number of trees in the forest, the maximum depth of the trees, and the minimum number of samples required to split an internal node are tuned. Grid search involved defining grids of possible values for each hyperparameter and evaluating the algorithms performance on a validation set for each hyperparameter combination. The optimal set of hyperparameters, resulting in the best performance, is selected as demonstrated in Table 3. The linspace is a function used to create an array of evenly spaced spaced between a specified starting point and ending point. The format of linspace can be described as *linspace*(*start*, *end*,*num*), where "start" represents the initial value, "end" represents the final value of the array, and "num" indicates the length of the array.

ANNs are initialized with random weights before training to prevent the network from being trapped in local minima during optimization. The primary aim is to ensure the models' effectiveness and reliability, which is achieved by actively pursuing convergence of results. This pursuit involves fine-tuning the models to attain an optimal performance state where they learn data patterns adeptly, avoiding overfitting and training issues. As a result, the models gain robustness and dependability in real-world scenarios. Once the ANN models are trained, they are subjected to real-time simulation tests, showcasing their impressive performance. This success serves as evidence of the models' convergence and proficiency.

The chosen evaluation criteria R^2, MAE, MSE, RMSE, and response time (prediction time) are specifically adopted to comprehensively measure the model's predictive accuracy and efficiency. Where R^2, quantifies the proportion of the variance in the dependent variable that is explained by the model's predictions. MAE computes the average absolute difference between the predicted values and the actual values. It provides a straightforward measure of the model's prediction accuracy. MSE calculates the average of the squared differences between predicted and actual values. Squaring the errors amplifies larger errors, making MSE sensitive to outliers and providing a measure of the average squared magnitude of errors. RMSE is the square root of the MSE and shares its characteristics while also being on the same scale as the original target variable. RMSE provides insight into the typical size of the prediction errors. The response time reflects the computational efficiency of the model during inference. It measures the time taken by the model to generate predictions once it's deployed. A lower response time is desirable for real-time applications and responsiveness. All evaluation criteria are taken into consideration while evaluating the models developed in the study. However, since the developed models will be run in real-time application, response time and R^2 are given more importance. The pseudo code of training ANN with gridsearch is is summarized as given below.

Algorithm : Pseudo Code of Training ANN With GridSearch

Define *The hyperparameters of ANN and their possible values*
Number of Hidden Layers = [1, 2, 3]
Number of Neurons in each Hidden Layers = [1, 2, 3, ……, 10]
Learning Rates = [0.0001,0.0005,0.001,0.005,….,1]
Create *a grid of all possible combinations of hyperparameters*
Initialize *variables to store the best model, combination and performance*
Split *the Training Dataset to training and validation randomly*
Loop *through each combination in the grid*
Create a neural network model with the current combination of hyperparameters
Starts the weights of Model Randomly
Train the model on the training set
Evaluate the model on the validation set
IF *the performance is better than the best performance*
update the best performance, model and combination
End IF
End Loop
Return *The best performance, model and combination*

3. Research findings

The research findings of the study are examined in two stages, and in the first stage, the datas are trained with ML on the data set obtained from the BLDC engine. In the second stage, the estimation results are obtained by applying the most successful ANN ML model on the speed-sensorless DTC of BLDC motor in simulation.

Table 4
ML-based perdictors performance results.

Model	R2 (%)	MAPE (%)	MAE	MSE	RMSE	Response Time (ms)
ANN	**99.85**	**0.21**	**0.911**	**1.423**	**1.193**	0.014
RF	99.2	0. 84	0.094	0.478	0.0691	0.61
k-NN	97.2	2.75	4.068	10.392	108.003	**0.012**

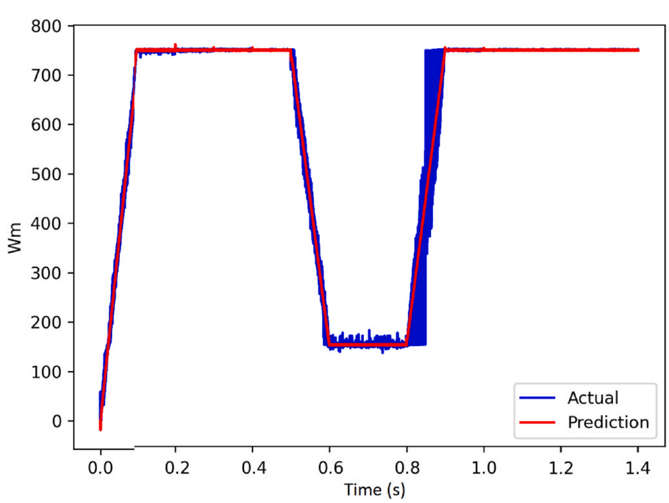

Fig. 4. K-NN-based estimators performance on test data.

3.1. Results from ML models for the BLDC dataset

In the study, ML-based BLDC speed estimators were developed. The performance results of the developed ANN, RF and k-NN based

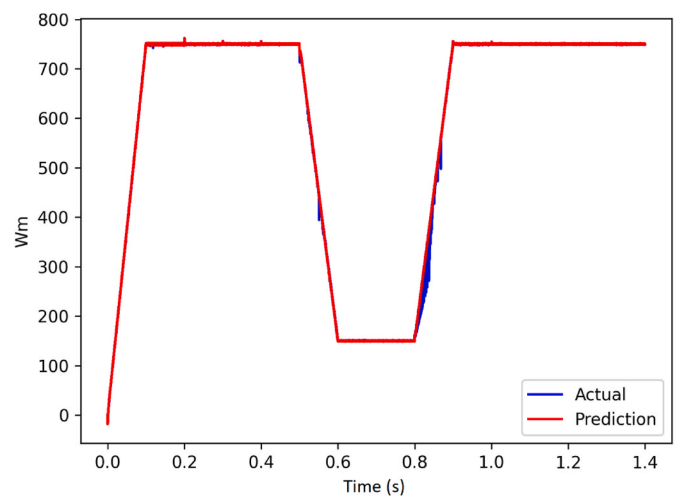

Fig. 5. RF-based estimators performance on test data.

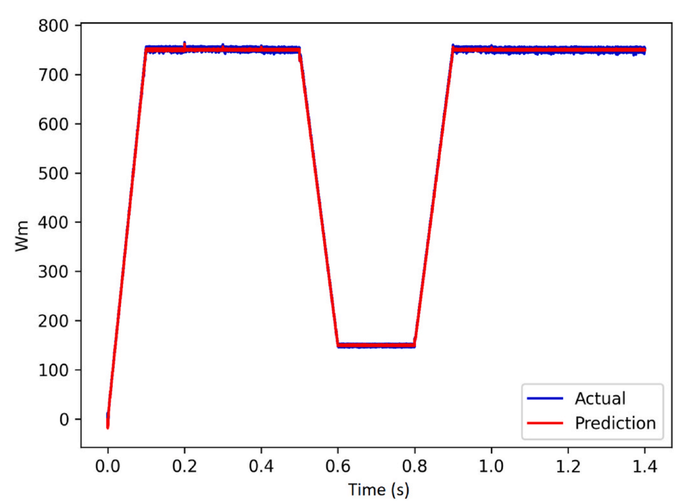

Fig. 6. Proposed ANN -based estimators performance on test data.

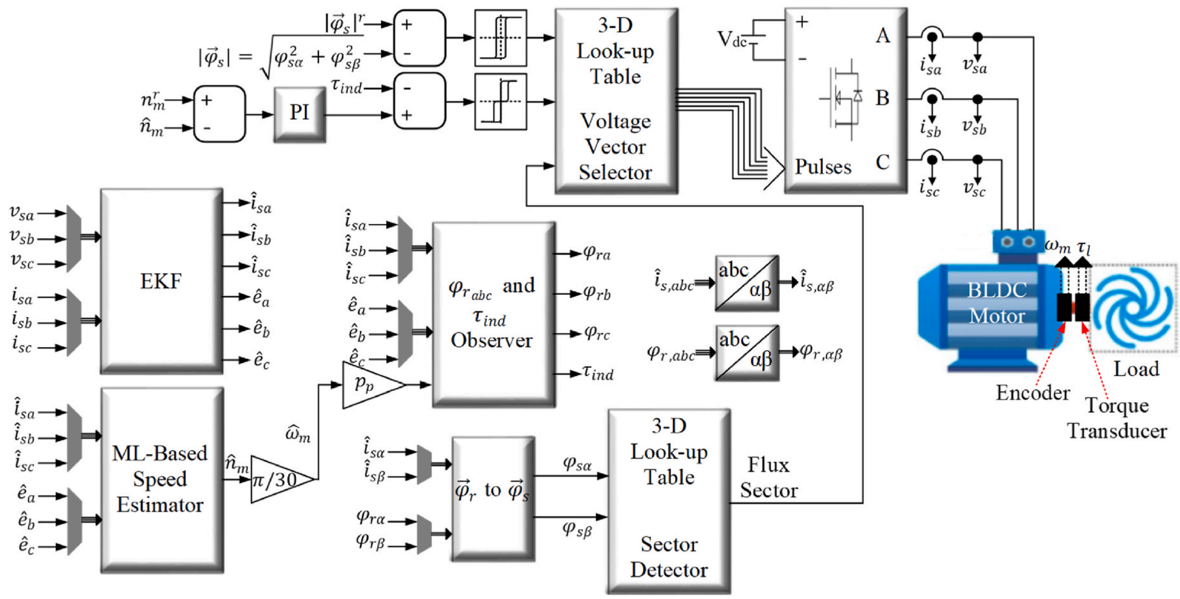

Fig. 7. Speed-sensorless DTC drive system of BLDC motor.

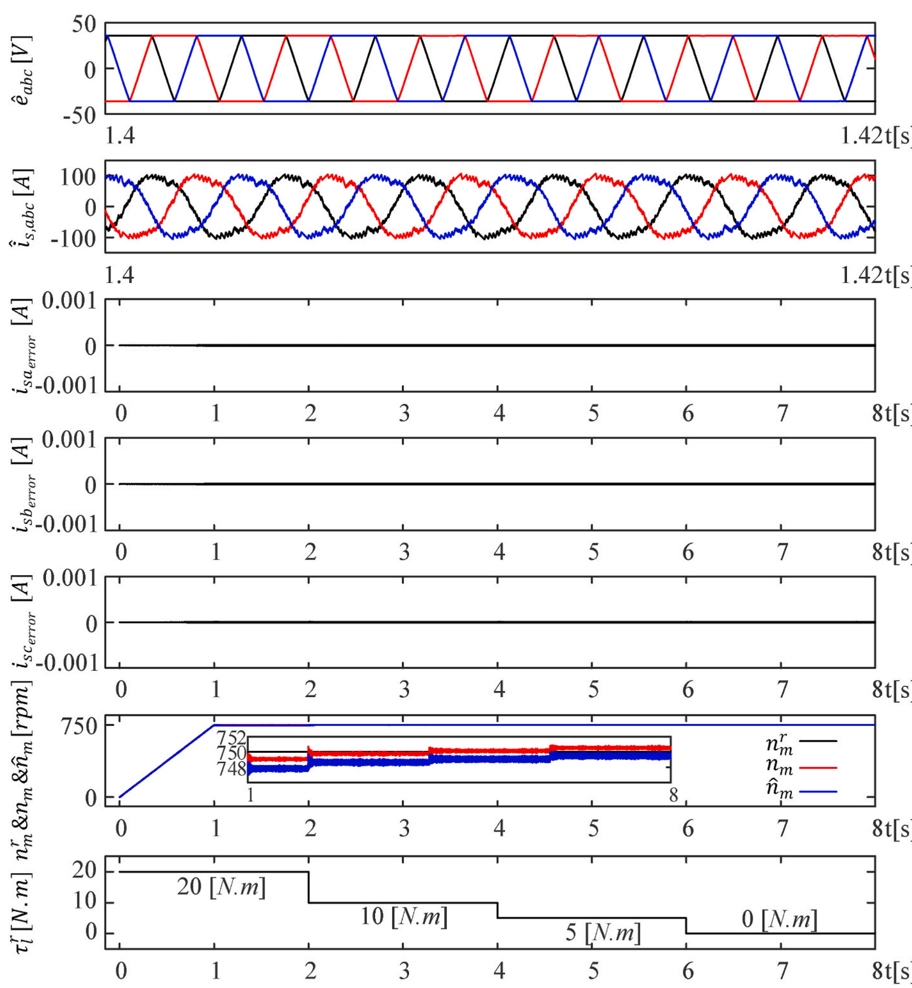

Fig. 8. Simulation results on estimation and control performance of the proposed hybrid estimator-based speed-sensorless DTC drive system of BLDC motor at high speed.

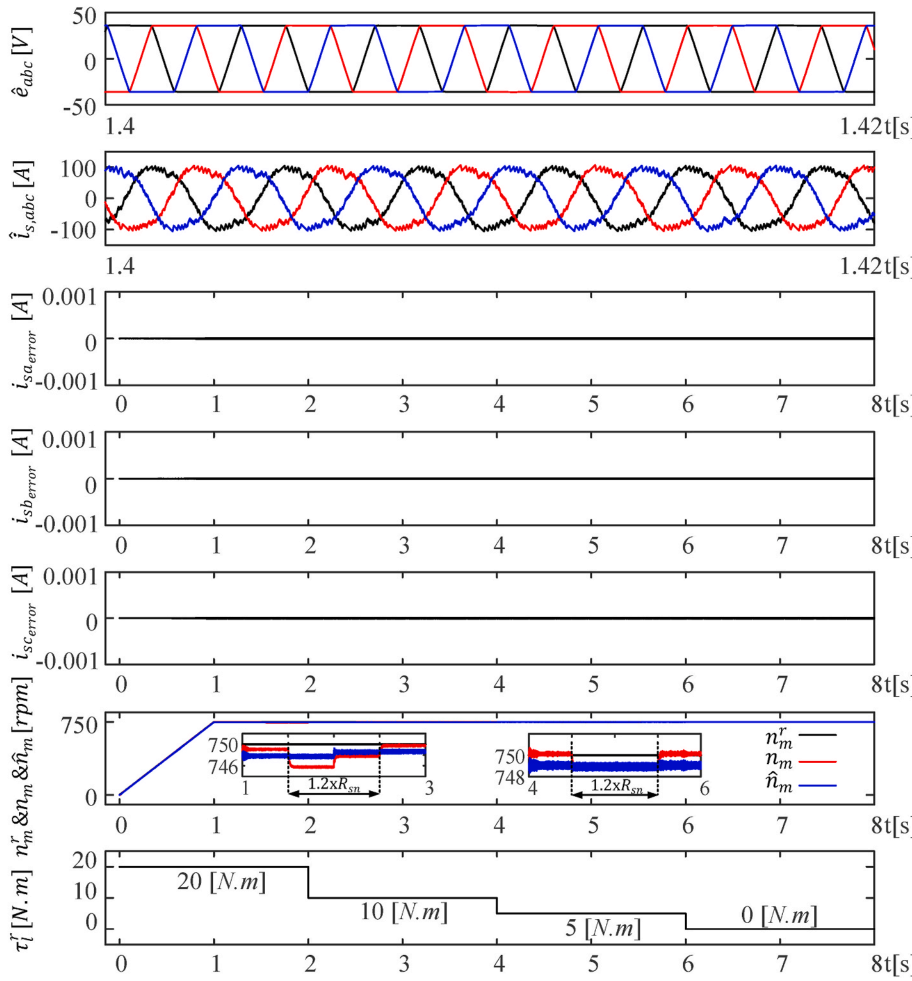

Fig. 9. Simulation results on estimation and control performance of the proposed hybrid estimator-based speed-sensorless DTC drive system of BLDC motor at high speed while R_s is changing.

estimators was evaluated by to R^2, MAE, MSE, RMSE, and response time performance evaluation criteria, and the results are given in Table 4.

Table 4 displays the results of the experiments conducted using different ML methods. The ANN model has achieved the highest scores in terms of R^2, MSE, RMSE, and MAE, indicating superior performance. On the other hand, the k-NN algorithm performed the best in terms of time response, obtaining the highest score among all methods for this particular dataset. The testing results of the ML-based models developed in the study are presented in Figs. 4–6, showcasing their performance on the test dataset. Upon analyzing Figs. 4–6, it is evident that all estimators have achieved favorable results. Nevertheless, the ANN emerges as the top-performing estimator among them.

3.2. Simulation results on the estimation performance of the proposed ML and EKF-based estimators

The proposed ML-based speed estimator and the EKF-based estimator proposed for the estimations of i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c states/parameters of BLDC motor are tested on a speed-sensorless DTC drive system in simualtion as shown in Fig. 7. A novel hybrid estimation method is proposed by using two different estimators together. Thus, a new ML-based speed estimation method can produce a solution to an industrial problem and a new EKF-based estimation method is introduced to the literature as a result of the needs of the proposed ML-based speed estimator.

In the speed-sensorless DTC drive system of BLDC motor, φ_{ra}, φ_{rb}, φ_{rc}, and τ_{ind} are observed by using the estimated values of i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c obtained from the proposed EKF algorithm. The three-phase rotor fluxes and stator currents are converted to stator stationary axes (-$\alpha\beta$) by Clarke transformation. Flux sector is determined with 3-D look-up table by using the $-\alpha\beta$ components of rotor flux and stator current. During this procedure the stator flux is calculated from the $-\alpha\beta$ components of rotor flux and stator leakage flux which derived from the stator leakage inductance voltage drop. Moreover a PI-type speed controller is used to generate the reference value of the τ_{ind} and two and three level hysteresis comparator are used to determine flux and moment response of the drive system, respectively. At the end of the DTC the voltage space vector is determined with a 3-D look-up table which is used for the switching conditions of 3-phase inverter as shown in Fig. 7.

The proposed hybrid estimator is tested on a speed-sensorless DTC drive system of a BLDC motor at two different speed region defined at high speed and low speed while R_s is varied to 1.2 times of its rated value and kept as constant at its rated value under mechanical load torque (τ_l) variations. In Figs. 8–11, $.^r$ and $\hat{}$ represent the reference value and estimated value, respectively.

A- Estimation and Control Performance Test of The Proposed Hybrid Estimator-Based Speed-Sensorless DTC Drive System of BLDC Motor at High Speed.

In this scenario, the BLDC motor is accelerated from zero speed to rated speed (n_r=750 rpm) under rated load torque (τ_l=20 N m). The speed of the BLDC motor is kept constant at its rated value during 8 *s*. During this scenario, τ_l is reduced to 10 N m at 2. *s* and 5 N m at 4.s, and τ_l is completely removed at 6. *s* while R_s is kept constant at its rated value as shown in Fig. 8. Depending on the load torque change, it is observed

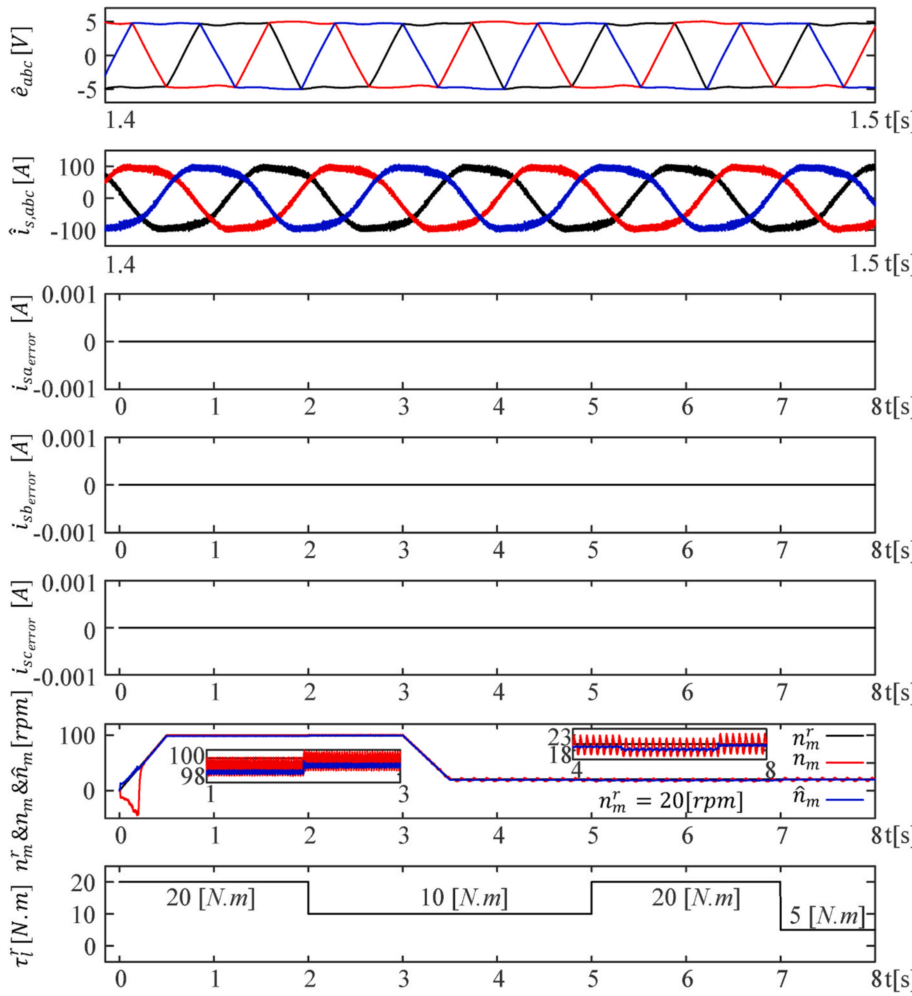

Fig. 10. Simulation results on estimation and control performance of the proposed hybrid estimator-based speed-sensorless DTC drive system of BLDC motor at low speed.

that both the $\hat{n}_m$ represented with blue line and the n_m represented with red line converge much more to the reference value of the speed (n_m^r) represented with black line due to the decrease in τ_l, and when the overall scenario is considered, both the $\hat{n}_m$ and the n_m converge to n_m^r with a very low error.

By repeating this scenario involving high speed operation, R_s is increased to 1.2 times its rated value at 1.5 $s<t<2.5$ s and 4.5 $s<t<5.5$ s time intervals to test both the estimation performance of the proposed hybrid estimator and the speed control performance of the DTC against the R_s variations as shown in Fig. 9. It is seen that the R_s change does not cause major errors in both speed estimation and speed control, since the effect of voltage drop due to R_s on the back-emf induced in the stator is weak at high speeds. All these results show that the proposed mixed estimation method and DTC method have high estimation and control performance during operation in high speed regions.

In addition, it is clearly seen in Fig. 9 that the ML-based speed estimator can tolerate the errors that are occur in the i_{sa}, i_{sb}, i_{sc}, e_a, e_b, and e_c estimations obtained from the proposed EKF-based estimator depending on the R_s variations.

B- Estimation and Control Performance Test of The Proposed Hybrid Estimator-Based Speed-Sensorless DTC Drive System of BLDC Motor at Low Speed.

This scenario is set up to test the estimation performance of the proposed hybrid estimator method, as well as the speed control performance of the DTC when the BLDC motor is running at low speeds and the results of the test scenarios are given in Figs. 10 and 11. For this purpose, first of all, the BLDC motor is accelerated to a speed of 100 rpm (n_m^r =100 rpm) under the rated τ_l=20 N.m. In the 0.5 s<t<3 s time interval, the motor is kept constant at 100 rpm. While the BLDC motor is running at 100 rpm, τ_l is reduced to 10 N m at 2. s. The BLDC motor started to slow down at 3. S while τ_l=10 N m and is operated at a speed of 20 rpm (n_m^r =20 rpm) at a time interval of 3.5 s<t<8 s. While the BLDC motor is operating at a speed of approximately 20 rpm, τ_l is reduced to 5 N m at 4. s and the motor is start to operate under no-load at 6. s.

In addition, the estimation and control performance of both the proposed hybrid estimator and the DTC of the BLDC motor are tested against the R_s variations while the BLDC motor is running at low speed. The results of this scenario are presented in Fig. 11 The scenario presented in Fig. 11 is the same as the scenario presented in Fig. 10, but unlike the scenario presented in Fig. 10, only R_s variations are generated at some time intervals.

As presented in Fig. 11, the R_s is increased to 1.2 times its rated value at 1.5 s<t<2.5 s and 4.5 s<t<5.5 s time intervals. Especially operation at very low speed, although the ML-based speed estimator has high estimation performance, the speed control performance is become unstable due to the weakening of the estimation performance of the proposed EKF-based estimator due to the voltage drop effect, which is of great importance at low speeds, depending on the R_s change. However, as soon as τ_l is decreased to 5 N m the speed control performance is also achieved while R_s is defined as its rated value to the BLDC motor model.

As a result, it is understood from the simulation results that the

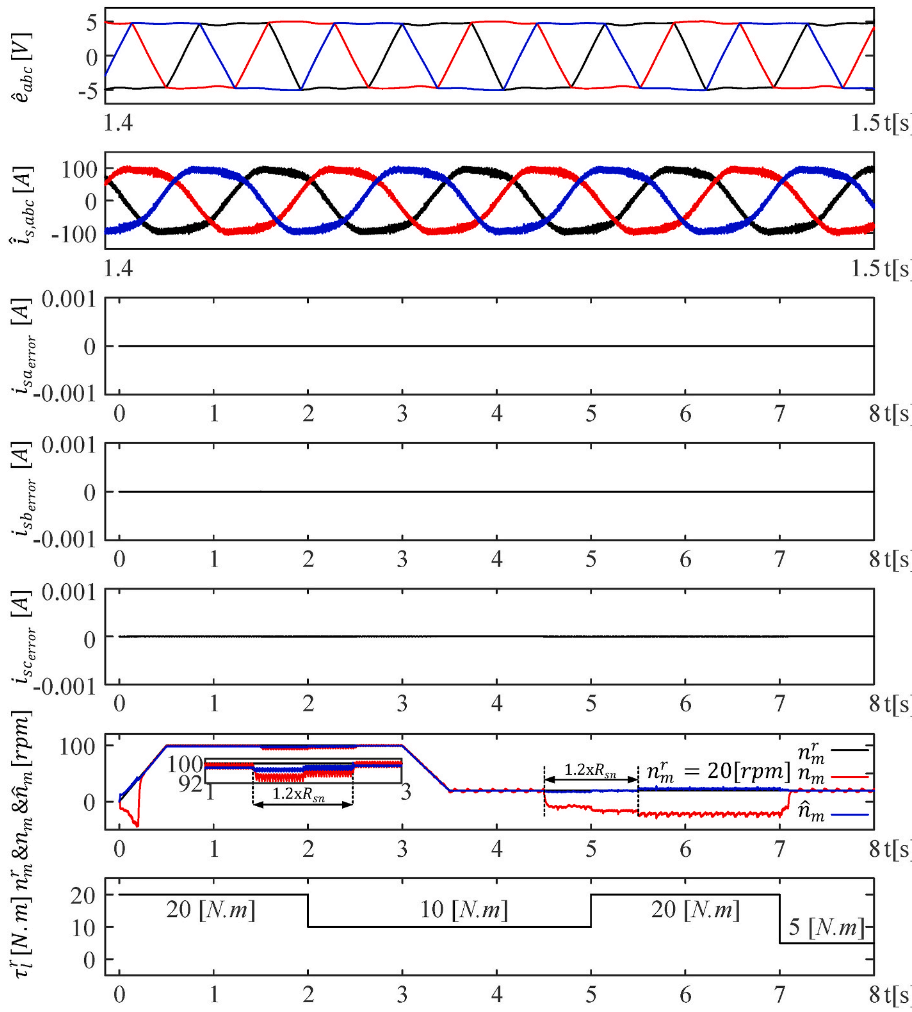

Fig. 11. Simulation results on estimation and control performance of the proposed hybrid estimator-based speed-sensorless DTC drive system of BLDC motor at low speed while R_s is changing.

proposed hybrid estimation method has remarkable errors when R_s variations occur only in the low speed region, but these errors can be tolerated by the ML-based speed estimator, and thus the proposed hybrid estimator has a very high performance especially on speed estimation.

4. Discussion

When the academic literature related to the study is examined, BLDC motors have started to be used extensively in the electric vehicle, aerospace industry and medical and automotive robot industries due to their stable speed-torque characteristics, quiet operation, long life and efficiency (Becerra and Ehsani, 1988; Kim et al., 2006). However, such applications require BLDC motor speed and rotor position information (Celikel, 2019). In traditional methods, the measurement of rotor speed and position is provided by hall-effect sensors or incremental encoders. The use of these sensors requires physical interventions to the motor and this case increases the cost of the driver and deteriorates the driver's stability (Matsui and Shigyo, 1992). For this reason, estimation of rotor speed and position is preferred. For this purpose, various estimation methods have been proposed by using stator voltages or back-emf information (Iizuka et al., 1985; Tsotoulidis and Safacas, 2012). The proposed methods for measuring the back-emf, are limited in speed control performance in low speed operation (Damodharan and Vasudevan, 2010; Moreira, 1996; Gamazo-Real et al., 2022). For this reason, the Kalman filter, which is compatible with the dynamic nature of the BLDC motor as mentioned in Gamazo-Real et al. (2022) and triggers the estimation performance by taking into account the system and measurement noises. In this study an EKF-based estimator is proposed for the estimation of the back-emf of BLDC motor. In the study done by (Li et al., 2022) they introduces a new hybrid forecasting model called SHM CNN–GRU–AM (SHM-C&G&A), designed to improve the accuracy of ship motion prediction. The model combines a Convolutional Neural Network (CNN) for spatial feature extraction, a Gated Recurrent Unit (GRU) to capture temporal patterns, and an Attention Mechanism (AM) to control feature contributions. The paragraph also mentions the development of a hybrid genetic cloud whale optimization algorithm (GCWOA) to optimize the model's hyperparameters. The proposed approach, GCWOA-SHM-C&G&A, is demonstrated to be more robust and effective in forecasting ship heave and pitch motion compared to other models. The GCWOA algorithm proves superior in optimizing hyperparameters for improved forecasting performance Li et al. (2022).

Upon reviewing the relevant academic studies, it is observed that the estimation of various states and parameters of the BLDC motor is addressed in relation to the Kalman filter. However, the literature indicates a scarcity of extensive academic research on the application of ML in parameter estimation and speed estimation for BLDC motors. ML and AI-based speed and position estimators proposed in the literature are examined in detail in the first section defined as Introduction, and the methods proposed in the mentioned studies are evaluated with different aspects. Consequently, the ML-based estimation model is developed in this study for estimating the rotor speed of the BLDC motor.

During the development of the proposed ML-based speed estimator, different training algorithms are used with ML-based estimator and these training algorithms are compared to each other about the training achievements, algorithm complexity and speed and estimation accuracy as carried out in Xu et al. (2023). Also it is expected to introduce a fresh perspective to speed sensorless dynamic control systems, which are already documented in the academic literature.

5. Conclusion

In various industries such as robotics, automotive, and aerospace, achieving stable dynamic control of speed-sensorless BLDC motors is crucial for enhancing energy efficiency. Model-based estimation algorithms are commonly employed for speed estimation in BLDC motors. However, these estimation algorithms also necessitate the estimation of different states and parameters associated with the BLDC motor.

In this study, a unique dataset is generated from current and back emf values obtained through a novel EKF-based estimator in a simulation environment specifically developed for BLDC motors. The dataset is then utilized to perform speed estimation of the BLDC motor using ML methods such as ANN, RF, and KNN. The following results are obtained from the application of these ML methods on the created dataset for speed estimation of the BLDC motor.

- This study evaluated the performance of the ANN, RF, and KNN ML algorithms using various performance evaluation metrics such as R2, MAPE, MAE, MSE, and RMSE. The ANN ML model achieved the highest accuracy rate of 99.85% among the evaluated models.
- In terms of response time within the ML-based system, the KNN ML algorithm is found to be the most successful with a response time of 0.012 ms when compared to the ANN and RF algorithms.
- Simulation studies revealed that the hybrid estimation algorithm developed in the study exhibited a high convergence speed.
- The proposed hybrid estimation algorithm demonstrated a high estimation performance, which has a positive impact on the dynamic control of the speed-sensoeless BLDC motor.
- Furthermore, the simulation results indicated that the proposed ML-based speed estimator model shows minimal sensitivity to parameter changes. Even with parameter variations, the model maintained a robust structure and exhibited consistent estimation performance.

Upon evaluating the aforementioned results in the study, it is believed that the ML-based speed estimation model developed for the BLDC motor has the potential to be applied across various industrial domains due to its advantages in terms of speed, time, control stability, and cost. Future research endeavors aim to expand the scope by employing ML models to estimate different parameter variations in the BLDC motor. This would further enhance the applicability and adaptability of the proposed estimation approach in practical settings.

Furthermore, it is aimed to realize the hybrid estimation method proposed in this study for the dynamic control of high efficiency permanent magnet synchronous motors, which have started to find wide application area in the defense and industrial sectors such as manned or unmanned electric vehicles, and whose popularity is increasing nowadays. In addition to these, estimation of different motor parameters that vary depending on temperature and the effect of saturation in the core with different ML-based methods is also aimed by the authors in future studies.

CRediT authorship contribution statement

Remzi İnan: Carried out a literature review, Brushless Direct Current Motor simulation application, Writing – review & editing. **Bekir Aksoy:** Carried out a literature review, Machine Learning modeling, Writing – review & editing. **Osamah Khaled Musleh Salman:** Carried out a literature review, Machine Learning modeling, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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