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Original Article

Speed Estimation of a Direct Current Motor Based on a Convolution Neural Network

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Abstract
Electrical motors have been engaged in many residential, industrial and commercial applications. The speed of an electric motor is an essential output quantity which is needed in many processing systems. Therefore, estimating the speed of an electrical motor is an integral part in the hierarchy of operational and control process. In this work, a new speed estimation method is proposed which is based on a naturally occurring signal; the mechanical vibrations the body of the motor endure during operation. These vibration signals are measured in multi-axial dimension through accelerometer and gyroscope. Furthermore, the collected data is trained in a machine learning model. The model is used subsequently to estimate the speed of a self-excited direct current (DC) motor. Two approaches (offline and onboard) are followed to evaluate the fitness and the performance of the proposed method. The offline approach is performed using regression learner MATLAB toolbox and many algorithms are tested and results with different performance metrics are presented. The algorithm that yields best performance in terms of minimum Root Mean Square and maximum regression factor (R^2) is selected as candidate for offline revolutions per minute (rpm) estimation. Results documents that with Gaussian process regression algorithm, estimations are obtained with a mean square error of 7 rpm and an R^2 value of 1 which is considered a very satisfactory performance. The second approach is motor speed estimation in real time using vibration signals with deep learning model implemented on limited resources electronic board which is proposed for the first time to the best of our knowledge. The proposed method has been successfully implemented by low consumption resources from the selected board with 6.5 kb of ram and 91ms latency. Even with the limited resources, a rated speed estimate percentage error of 0.18% was recorded from real time results. Moreover, the proposed method is characterized by its simplicity, low technical requirements and eventually low cost of implementation. The aforementioned features make this method an attractive platform for speed estimation in many industrial applications.

Keywords
Motor Speed Estimation, TinyML, Gaussian Process Regression, Real Time, Embedded Devices.

I. Introduction

Even with modern technology, the electric motor remains a dominant player in applications that may not even be countable. An essential output parameter in the electromechanical conversion process, which the motor performs, is the speed. The value of the speed is employed in many processes such as control and compensation systems. Estimating the speed of a motor under varying technical conditions is mandatory so that other systems interfaced with motor may operate correctly and/ or efficiently. Traditionally, speed estimation started with methods that employ sensors. However, those methods suffer from numerous disadvantages such as; wirings venues, significant inaccuracies and reliability issues [1]. Sensor-less estimation of speed is an attractive alternative that has alleviated considerably many of the aforementioned drawbacks mentioned for sensor-based estimation [1, 2]. Sensor-less speed estimation is based on a two stage; a state observer and an estimator which is commonly referred to as adaptive methods [3]. Numerous approaches have been put forward in the field of Sensor-less speed estimation which consider Kalman, extended Kalman filters, artificial neural networks and model reference adaptive system (MRAS) [3, 4]. The adaptive method basically estimates the speed of the motor based on the stationary frame $\alpha\beta$ components of stator flux. These flux components are first calculated from a reference state space model. Then, another model, which is augmented by an error term, estimates those fluxes. Finally, the speed is estimated based on an adaptive method that minimizes the error between calculated and estimated fluxes. Authors report that although the obtained estimations of speed are characterized as an effortless , speedy estimates but degraded accuracy. Estimation based on the mathematical model of the machine is an approach that confine the estimate to the parameters of such a model [5, 6].

Some of the drawbacks related to the Senor-less speed estimator can be healed by the using the saliency harmonic tracking (SHT) [7, 8]. The main idea behind this method is to track the harmonics generated through the non-uniformity of inductance as function of rotor position [4]. Implementation of this method is speed range oriented. For high and medium speed estimation, mathematical models which predict the EMF in a motor is normally used [4]. Small or near zero speeds are estimated through saliency by injection of a voltage signal in rotor side. Since the inductance is not uniform (if induction motors are considered), a set of harmonic currents are generated which implicitly contain rich information regarding the rotors' position. If harmonics are tracked correctly an idea about the rotor position can be deduced. Although the accuracy of the estimation in SHT in not correlated to variation of motors' parameters, yet the method is not fully suitable for speed estimation since the high frequency injected signal results in noise and ripple torque [4], not to mention the caution that must be exercised when selecting the frequency of the latter mentioned signal. Artificial intelligence methods reflected mainly by neural networks (NN) have been used in both SHT [4] and adaptive sensor-less speed estimation [9,10]. In the former, neural networks can be used to detect the amplitudes of harmonics in case of small magnitudes that may not be correctly picked up by conventional tracking methods in the presence of noise. While [9, 10] use NN to enhance MARS performance.

An approach of sensor-less speed estimation is presented in [11] that employs the control signals of the complementary power electronics converters which are integrated with the motor. Authors consider a doubly feed induction generator that has two converters; at grid and rotor sides. Control signals of both or one of these converters are analyzed in spectral terms. A portion of the spectrum content is function of the rotor speed. This portion is identified, maximized and analyzed in order to extract the speed value of the generator. Authors report that accurate estimations are obtained at high speed ranges however, this accuracy is impeded at light loading of the induction generator. Recently, deep learning techniques have been used to estimate the speed of electric motors [12,13] and electric vehicles [14]. In [12], the speed of a brushless motor is estimated based on an extended Kalman filter which estimate the back EMF as a first step. Then a large set of input current and estimated EMF data are used to train a neural network where the targets are the corresponding sampled speeds. Once trained, the neural network can estimate the speed for any measured current and estimated back EMF. Authors report a speed estimation characterized by high accuracy speed and subsequently those estimations are used in direct torque load control system. Work presented in [13], dealt with providing rotor position estimations of a permeant magnet synchronous motor through a machine learning based observer. Two sets of data are obtained; one for training purposes, a process implemented by Elman neural network (ENN) and the second is for testing. Good estimations are obtained for the rotor position, however, there is a need to utilize current and voltage sensors and an abc to $\alpha\beta$ stationary frame conversion stage. In [14], the speed of a vehicle is estimated based on vibration signals of the wheels and body of the vehicle. These vibrations are measured using three accelerometers that provide; longitudinal, lateral and vertical signals. A fourth signal represents the average yaw. Those signals are trained using a convolution neural network (CNN) with vehicle speeds as targets. Authors report accurate estimations in circumstances of fast speed changes and small range speeds.

Signatures related to motor operation have been used to extract information related to; speed, torque and /or efficiency [15–17]. In [15, 16], an image from a mobile camera has been used to measure motor speed. In [16] authors report a relative error of 0.6% in the measurement process. Sound signature in [17], were employed to provide speed estimations of an induction motor. Although the method is branded as simple, given the availability of the recording devices, yet the surrounding noise sources may hinder a correct estimation, although authors state that the recording device was placed too close to the motor set.

Vibration signatures were utilized in [18] to estimate the speed of an electric motor. An intelligent mobile phone device was mounted on the motor surface cover to capture those vibrations signals. However, the methods require spectral content analysis in order to extract the rotor frequency which is used to provide a speed estimate. Moreover, at low speeds, the rotor frequency maybe hard to determine and may eventually constrain the estimation process. Authors report estimation accuracy error of 0.13% for rated speed estimation.

In this work, the speed of a DC motor is estimated based on a new approach that employ deep learning techniques. The approach in this work is based on measuring a multi-dimension vibration markers that are utilized as raw data for speed estimation. The main contribution of this paper can be highlighted in the following points;

1. A Deep learning-based approach that employee low resources tools for speed estimation is presented.
2. The estimation is based on an effortlessly measured vibration signal.
3. An onboard process is implemented to build a model that reflects vibrations/speed relation. This model is constructed locally and deployed for future estimation of speed.
4. The proposed method eliminates any spectral analysis that may require extensive resources.
5. A systematic documentation of speed/vibrations relation is presented that is based on an offline mode regression process.

Approach presented in this paper is characterized by its simplicity, low cost of implementation and the fit to be implemented on DC and AC motors. Furthermore, the presented approach requires no voltage or current sensors.

Apart from the introduction, the rest of the paper is organized as follows, section two presents background theory on speed of DC motor and verification of speed -vibrations relationship. section three presents the proposed method, whereas, section four examines results and formulate discussions with comparative analysis. Finally, the paper presents conclusion drawn from the results provided in this work.

II. Background Theory

A. Mathematical Representation of Motor Speed

Speed of the motor is mathematically related to input voltage and load conditions among other factors. In this section, the speed of an electric motor is expressed mathematically to determine the factors the govern its behavior, Fig. 1 depicts a self-excited DC motor which supplies a torque load, T_L. The voltage balance around the armature terminals can be expressed as,

$$V_{in} = E_b + I_a R_a \tag{1}$$

Where, V_{in}, E_b, I_a and R_a are the input voltage, armature voltage (back EMF), armature current corresponding to a specified mechanical loading condition and armature resistance respectively.

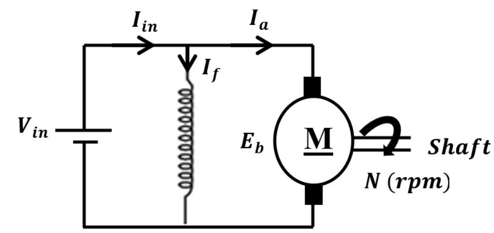


Fig. 1. Schematic of a self-excited DC motor

The back EMF is expressed as,

$$E_b = K_a N \emptyset \tag{2}$$

Here, K_a, N and $\emptyset$ are the armature constant which is dependent on the machine parameters, speed of armature in rpm and flux per pole respectively. By substituting Eq. 2 into 1, an expression of the motor speed can be expressed as,

$$N = \frac{V_{in}}{K_a \emptyset} - \frac{R_a}{K_a \emptyset} I_a \tag{3}$$

Equation 3 reveals that the speed has two terms; the left-hand term which represent the no-load speed formula and the second term represents the drop in speed due to the loading condition. Hence, a direct variation can be achieved by varying the input voltage of the machine. The only constrain in that aspect is the value of voltage must not exceed the rated voltage endured by the armature. Consequently, the speed can be varied all the way from zero to rated speed.

B. Verification of Speed -Vibrations relationship

Naturally, a motor possesses vibrations during normal operation. These vibration signals can alter depending on the status of motor's conditions such as, if the motor is at no-load or at load. By inspection, the vibration signals are felt around the whole yoke of the machine. However, to the best knowledge of the authors, no mathematical analysis has been formulated to document such a relationship. Spectral analysis of the measured vibration signals has been conducted to estimate speed based on frequency of the highest value [18]. In this work, the relationship between vibration signals and motor speed is documented empirically using regression process. In that context, the motor vibration signals are measured and stored for a range of speeds. Hence several data sets are accumulated. MATLAB/tool box is used to document if a relationship exists between the measured vibrations and rpm speed.

1) The Gaussian Process Regression

The Gaussian process regression (GPR) is a well-documented regression in deep learning applications [19]. The main feature of the GPR is the strong ability to capture data features regardless of how much bulk of data is observed for training purposes. The aforementioned feature is mainly due to the process being non-dependent on parameters. Moreover, GPR is based on a probabilistic distribution which can accommodate any uncertainty in the observed data. The purpose of using GPR is to determine a function, based on available observations, and then utilizing this function in providing estimation for points that are not within the sets of observed data. The observed data in this work represents the vibration signals measured from the motor that include readings of accelerometer and gyroscope. If a set of vibrations, in a specific sample, are denoted as, V^1 and V^2, with speeds $N(V^1)$ and $N(V^2)$ respectively, then both $N(V^1)$ and $N(V^2)$ are jointly Gaussian distributed. Therefore, both of these outputs (or functions) are defined in terms of Gaussian as,

$$\begin{pmatrix} N(V^1) \\ N(V^2) \end{pmatrix} \sim (\mu, K) \tag{4}$$

Here both functions are standard normal variable with mean, μ and covariance K. Both μ and K can be utilized to shape the function needed for regression. For example, if V^1 and V^2 are vibrations that are measured at speeds that are close together, then it is expected that $N(V^1)$ and $N(V^2)$ are correlated strongly. Hence, the regression function required based on the Gaussian multivariate is defined as,

$$\begin{pmatrix} N(V^1) \\ N(V^2) \end{pmatrix} \sim N\left(\begin{pmatrix} m(V^1) \\ m(V^2) \end{pmatrix}, \quad \begin{pmatrix} k(V^1,V^1\ ) & k(V^1,V^2) \\ k(V^2,V^1) & k(V^2,V^2) \end{pmatrix}\right) \tag{5}$$

Where, $m(V^1)$ & $m(V^2)$ are the mean function for the observed vibrations sets. Here, the covariance function, $k(V^1,V^1)$ is a measure of the self-correlation between the two sets of observed vibrations, while, the function, $k(V^1,V^2\ )$ is a measure of the correlation between the vibration sets V^1 and V^2 [20]. There are a number of functions that are used for the covariance matrix determination, such as, exponential, double exponential, Matern 3 [20]. The mean function usually encodes any priori information about the function to be determined. The regression steps using GPR can be summarized as follows;

1. A prior distribution is assumed for the set of infinite functions that represent the expected outputs (in this case speed) for a set of input variables (vibration signals). This distribution is assumed without any observed data.
2. When observed data starts coming in, the function numbers are reduced from infinite to only those that provide the best fit of the current observed data. This will initiate what is called a posterior distribution.
3. When the observations are updated with new data, the current posterior distribution becomes a prior and an updated posterior is acquired.
4. The average function resulting from the posterior distribution of possible functions is the function utilized for future forecasting within the regression process.

2) Lite Deep Learning Model (TinyML)

Deep learning (DL) model usually consumed huge hardware resources to complete the given task and mainly work with devices like central processing unit (CPU) or graphical processing unit (GPU) because they have a powerful processing and computing abilities [21]. However, many applications over different range of disciplines require DL algorithms to handle the complex tasks and its not very feasible to use supercomputing power hardware to manage these tasks. Recently, new approach has been broadly developed to bring DL algorithm to be implemented on limited resource hard ware such as microcontrollers [22]. Less-demanding hardware resource DL algorithms have been developed so it can be deployed efficiently on microcontroller. The combination of lite DL algorithm and limited resources hardware are called TinyML [23]. Hence, TinyML may be an attractive platform for speed estimation of an electric motor. This is attributed to the low demanding resources a TinyML system requires.

III. The Proposed Speed Estimation Approach

A New approach for motor speed estimation is suggested for this work with the aid of machine learning algorithm. The proposed approach is designed to be implemented in low-cost hardware to estimate motor speed in real time. Fig. 2 shows the suggested steps for the proposed framework.

A. Hardware Installation

The self excited DC motor is selected to participate in speed estimation approach to cover more range of motors. For DC machine setup, a variable DC power supply with a range of 0-220V is used to energize the motor to achieve variable speed. The DC motor has the following rated specification: 220V, 2000 RMP, 0.3kW. The rotational speed is measured using optical tachometer with optical reflection mark fitted on the motor shaft.

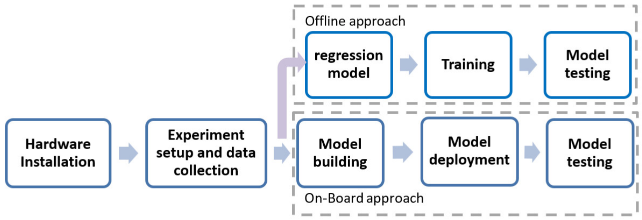


Fig. 2. Proposed approach

Hardware installation and the block diagram of the proposed work is shown in Fig. 3. Here, Fig. 3a shows a basic block diagram of the implementation, whereas, Fig. 3b shows the experimental setup. Moreover, to obtain the training data set, each set of vibration signals captured the corresponding speed is measured as shown in Fig. 3c. Finally, all experimental data is transferred to the data logger as shown in Fig. 3d of the experimental setup.

The vibration data is captured using Arduino Nano 33 BLE sense board [24]. This board is equipped with inertial sensors module LSM9DS1 (3D accelerometer and 3D gyroscope). This board is fitted firmly to the motor body using screws and nuts (sensors box) to guarantee the capturing of vibration with different speed range. The data is collected and stored on a laptop via USB cable and stored using Arduino IDE software [25].

B. Experiment Setup and Data Collection

The experiment is conducted to cover the full range of speed for the motor by controlling the power supply that energize the motors. For DC machine steps of 10% of full speed is chosen by changing the power supply DC level and at each step the speed is measured using optical tachometer with reflection marker fitted on the rotating shaft of the DC machine. At each step, the machine is kept running at the specified speed for 5 minutes (300 seconds) and Arduino board (Nano 33BLE sense) in that time measures accelerometer and gyroscope data. The data is stored in a file in the laptop using Arduino IDE software. Six values of each record (3D accelerometer and 3D gyroscope) are stored with sampling rate of 119Hz. An example of reading process is shown in Fig. 4. After experiment conduction, a time slot of 2000 ms is selected to build one sample by averaging the collected data in this time slot. The resulted dataset has more than 400000 records with 6 values in each record. Fig. 5, shows the speed with time during the experimental setup process.

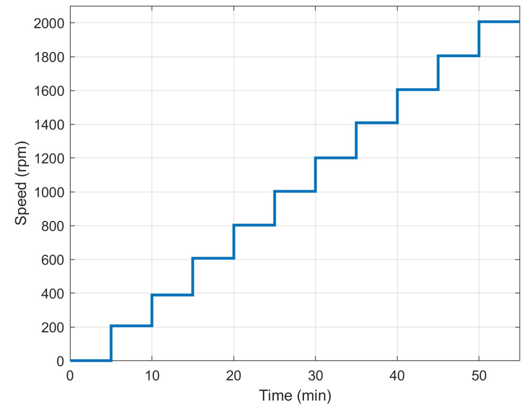


Fig. 5. Speed during experiment timing setup

C. Model Building

Online platform called EdgeImpulse has been used in this work for model building [26]. Feature extraction stage is added in this level to enhance the machine learning model performance. An fft spectral power analysis with 16 fft points is used to generate the features for each axis of accelerometer and gyroscope data as shown in Fig. 6. This results in 608 features for each of the 6 inputs data of variations record as shown in Fig. 4.

The 608 generated features are fed to a deep neural network, constructed from input layer which receives these features. Different sets of model hyper parameters are practiced to finally choose the structure based on performance training metrics. The deep learning neural network consists of two dense layers with 78 and 39 neurons in each respectively. The dense layer is fully connected layer that each neuron is connected to every neuron in preceding layer which helps to transfer the information and aggregate them to the next layer. The activation function is used with dense layer is rectified linear unit (RELU) function. A dropout layer with a rate of 0.2 is chosen to enhance the network performance and to overcome the overfitting issue.

This deep learning neural network is used as a regression stage to estimate the speed value based on the fed features. Hence, the last stage of this network includes one class that can predict continuous values of the estimated speed. The output layer uses SoftMax function to generate the predicted value of speed. A snap shoot of the neural network feature is shown in Fig. 7.

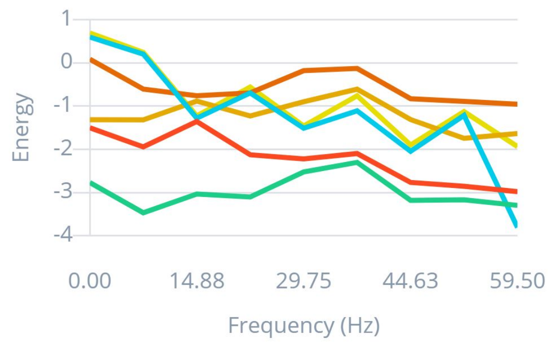


Fig. 6. Example power spectral feature generation stage

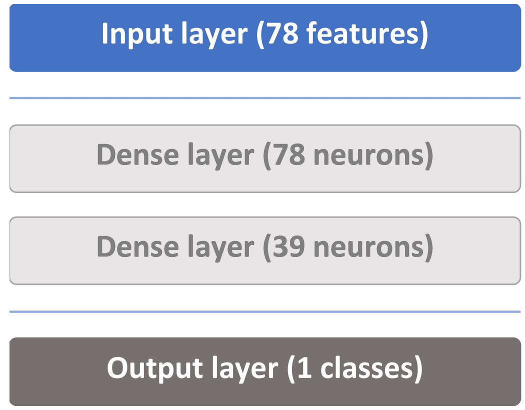
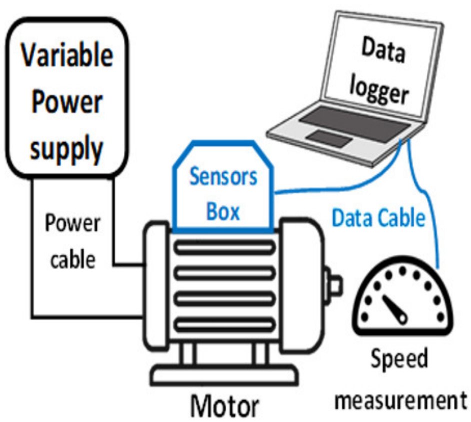
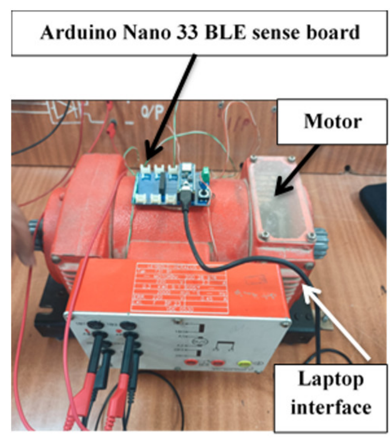


Fig. 7. Deep learning neural network structure

IV. Results and Discussion

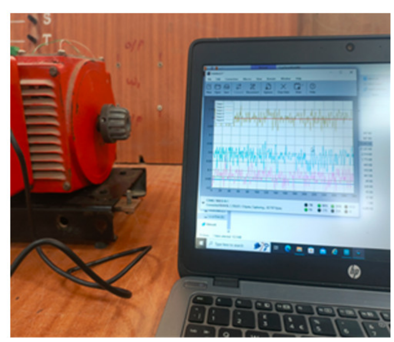


(a) Block diagram



(b) 33 BLE sense board to capture motor vibration

(c) Speed measurements



(d) Laptop for data accumulation and analysis

Fig. 3. Hardware installation of the proposed speed estimation approach

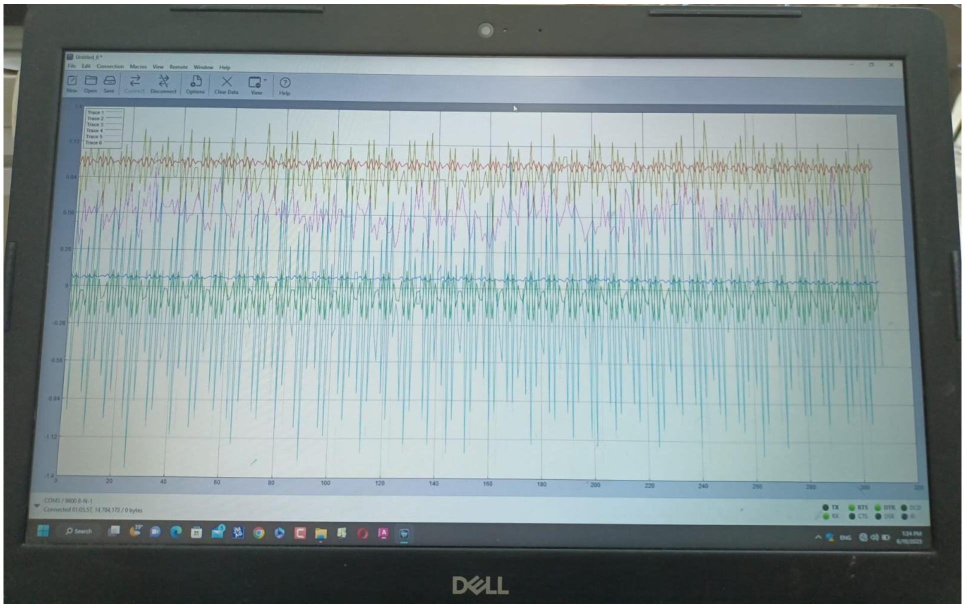


Fig. 4. Example of six value recording process

A. *Offline Method (Using MATLAB Regression Learner Toolbox)*

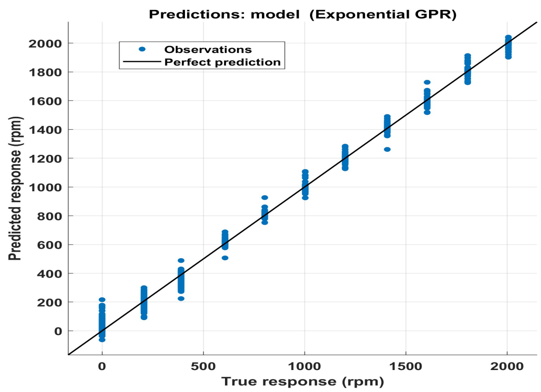
The collected dataset is used to generate 12 statistical features using 6 series of data (3D accelerometer and 3D gyroscope). Each series is fed to a moving average function and moving average standard deviation function with a window of 120 samples to generate the features set. The generated features are used to test the ability and fitness of proposed approach to estimate the motor speed based on its vibration components (accelerometer and gyroscope data). Using regression learner toolbox provided by MATLAB software, the data regression model is built and the performance metrics and error clearance are calculated. Different types of regression models (25 model) are tested using the calculated feature dataset and the results show variation levels of performance for selected regression models as shown in Table I. The metrics used for comparing regression algorithms are root mean squared error (RMSE), mean absolute error (MAE) and R-squared metrics. Table I depicts that Gaussian process regression (GPR- Exponential) and ensemble regression algorithm (Bagged tree) have gained the best regression performance metrics. RMSE for GPR- Exponential regression model has a value of 7.5 rpm which is very small error if it is compared to full range of motor speed (2000 rpm). Also, the R-Squared metric is almost 1 which is the perfect number and means that the estimated speed is very close to the actual speed.

Two out of 25 regression models are chosen based on their substantial performance metrics (RMSE and R-Squared). Three performance graphs for each regression model are chosen to demonstrate the relation between estimated and measured speed as shown in Fig. 8. The first graph (a, c) shows how the estimated speed values are distributed around the 11 measured speed values.

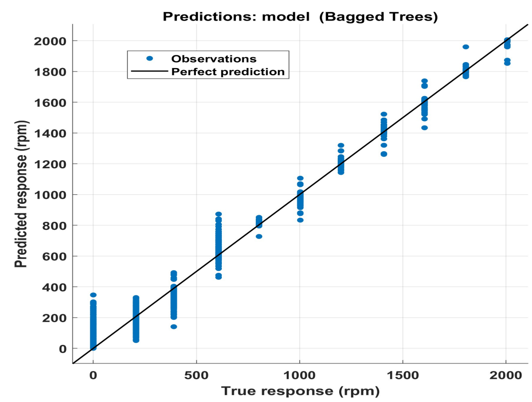
TABLE I.
PERFORMANCE METRICS OF DIFFERENT REGRESSION MODELS

Model type	RMSE (rpm) (validation)	MAE (rpm) (validation)	R-Squared (validation)
Tree	20.2207	2.126049	0.998983976
Linear regression	66.17129	44.46807	0.989119452
Tree - Fine	20.2207	2.126049	0.998983976
Support vector machine (SVM)	77.1826	57.36552	0.985196978
Ensemble (boosted trees)	69.68445	59.24658	0.987933443
Ensemble (bagged trees)	16.24997	3.994173	0.99934383
Gaussian Process Regression (Exponential)	7.576299	3.307598	0.999857365
Gaussian Process Regression (Rational Quadratic)	30.21451	13.4921	0.99773148
Neural network	49.70437	27.8393	0.993860957
Kernel	180.4167	129.4783	0.919115593
Kernel	69.17151	49.06138	0.988110433

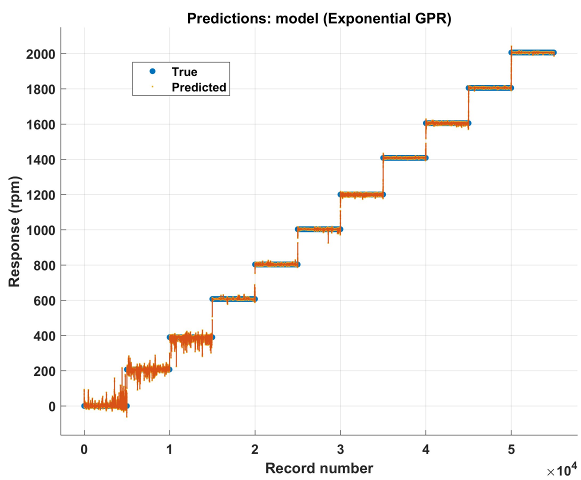
It is worth to mention that at higher speed the accuracy of speed values estimation is much better than the accuracy at



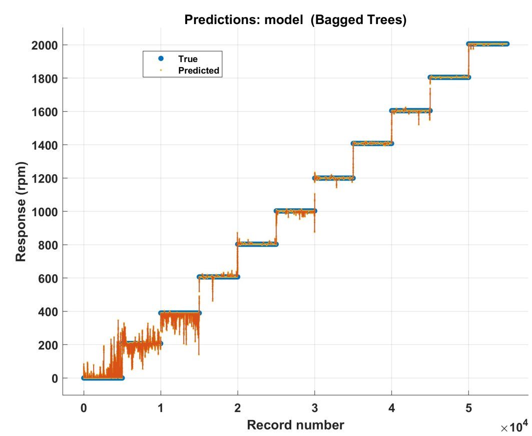
(a) Estimated vs measured speed



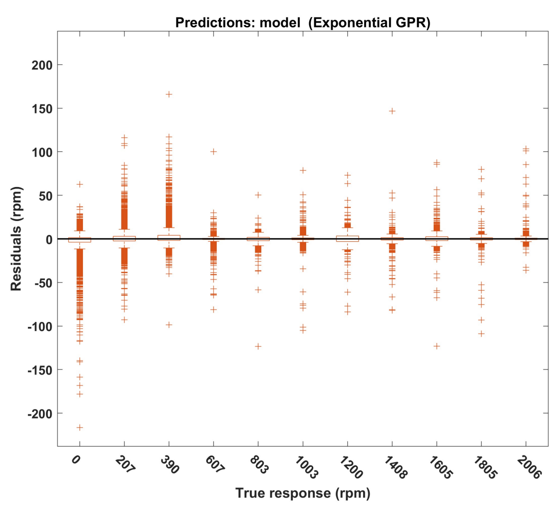
(b) Estimated vs measured speed



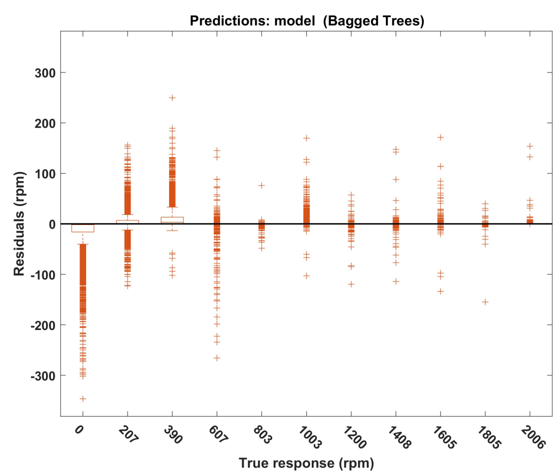
(c) Estimated and true responses



(d) Estimated and measured responses



(e) Residual error distribution



(f) Residual error distribution

Fig. 8. Two of the best regression model performance

lower motor speed values for both regression models graphs.

The second graph (b, e) illustrate how close are the estimated speed values to measured speed especially on categories close to rated speed. The last graphs (c, f) show the residual error distribution over measure peed categories in compare with estimated motor speed and again the graphs show clearly how these errors have higher values in low-speed values and vice versa.

B. Online method (onboard performance)

The collected data uploaded to an online machine learning developing platform (EdgeImpulse). The uploaded data which is consist of 6 time series is resampled to produce a dataset of 23 minutes and 7 seconds long. Each produced sample is one second in length with 104 subsamples inside. The resampled dataset is split into two parts: 80% for training and the remainder is for testing. The model is trained using training set and then its tested using the test set and the performance of the model is illustrated in Fig. 9. Two speed estimation models have been built to achieve an accurate motor speed estimator based on vibration signal which are regression model and multiclass model.

The regression model, which is built based on two dense layers and one dropout layer, has been tested using the test set to come up with accuracy of 97% and RMSE equal to 101.34 rpm.

However, the accuracy metric is measured based on a Maximum absolute regression error with threshold of 200 rpm. Different values of regression error threshold have been used to offer better overview and more elaboration about the regression model performance. Fig. 9 shows the accuracy level variation based on changing the error threshold with a range from 200 rpm, which is the common value as it is 10% of rated speed, to 40 rpm.

The model has been deployed on the selected hardware (Arduino Nano 33 BLE) and tested to evaluated the regression model performance and the required resources from the used board. Table II show the results in terms of used RAM, Flash and inference time. The regression model consumes a small part of the available resources and the model can produce the speed estimation with in less the 0.1 of a second. This result makes this estimator suitable for real time onboard motor speed estimation.

The second speed estimation model is the multiclass deep learning model. The motor full speed range is divided into 11 classes with 10% of rated speed each. Starting from standstill class and ending up to rated speed of 2000 rpm. The classifier confusion matrix is shown in Fig. 10 and the accuracy of the classifier is 90%. The confusion matrix depicts again the superiority of the estimator in higher speed over the performance close to standstill. The classification accuracy

TABLE II.
REGRESSION MODEL RESOURCES REQUIREMENT ON HARDWARE BOARD

	Spectral features	Regression	Total
Latency	87 ms.	4 ms.	91 ms.
Ram	6.5K	1.3K	6.5K
Flash	-	19.9K	-

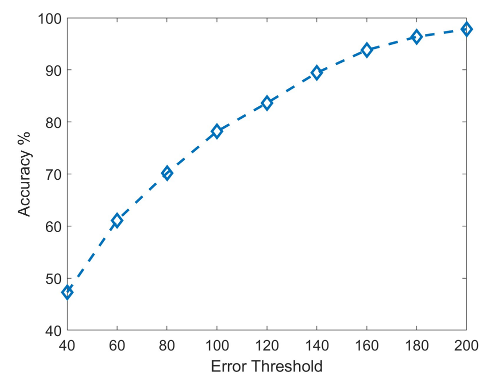


Fig. 9. Accuracy variation of Regression model for different values of threshold error

for classes close to rated speed almost 100% while they are around 75% when speed close to standstill. The F score performance metric is shown in the bottom of the graph which is an overall classifier performance metric and its values approve the same conclusion of the estimator performance related to speed class.

Multiclass speed estimator required less resources than regression estimator as shown in Fig. 11. Different combination of DSP blocks and deep learning hyperparameters had been tested to achieve better performance and minimum resources. The best combination is selected and tested to evaluate estimator performance. It can be noticed clearly that inference time is too short and in range of 27 ms and mostly consumed in the DSP block.

C. Discussion

The results of both methods (offline and onboard) show clear relation between vibration signals and motor speed. Moreover, the results of the two methods reveal the improvement of speed estimation accuracy at higher speeds and the best accuracy achieved at rated speed. The offline approach gains the best performance in terms of RMSE and R-squared metrics. The Gaussian Progress Regression (exponential) GPR model offers the pest RMSE with a value of 7.5 rpm which results in

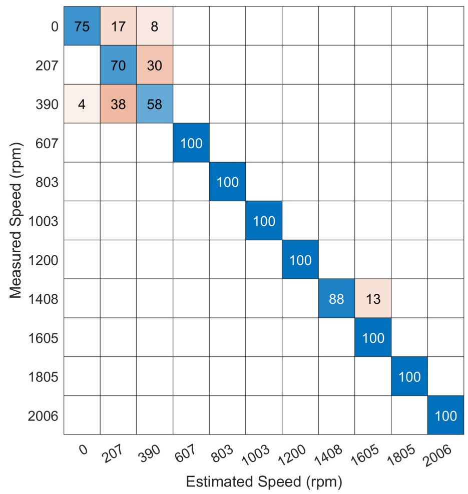


Fig. 10. Multiclass deep learning confusion matrix

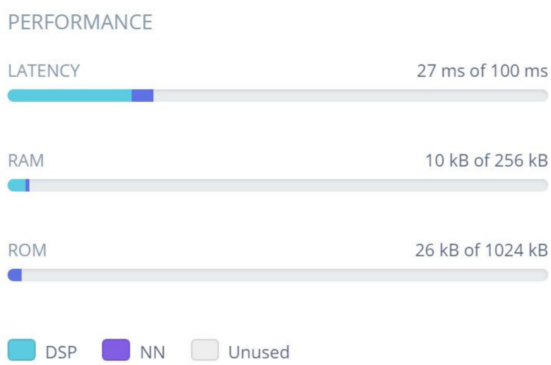


Fig. 11. Multiclass model resources requirement on hardware board

percentage error of

$$Error = \frac{|Actual\ speed - estimated\ speed|}{rated\ speed} \times 100$$
$$= \frac{7.5}{2000} \times 100 = 0.375\%$$

This percentage error clearly proves the success of proposed approach for motor speed estimation using vibration signals. The onboard method gains less performance metrics with RMSE of 101 and accuracy of 97% (based on a Maximum absolute regression error with threshold of 200 rpm). However, this method helps to deploy the proposed method on limited resources electronic board and make speed estimation method in real time applicable. Two machine learning models have been trained and tested using the collected data and they are regression and classification models. The regression model reveals better accuracy values with higher usage resources and latency time.

D. Comparative Analysis

In this section a comparative analysis is presented. The proposed method reveals many features that can be documented and utilized practically to obtain a local compact speed estimation system. The features, compared to other methods are outlined in Table III below. In this work, the estimation accuracy is documented in two situations. The first is by summing up all differences between actual and estimated rpm value along the entire range of speeds considered in this work; which is from zero to rated speed. In the second situation a comparison of estimation at rated speed is considered. In the latter, the estimated speed error, as depicted in Fig. 12, is found to be 3.6 rpm. Hence, the estimation error is calculated as,

$$\frac{|3.6|}{2000} \times 100 = 0.18\%$$

This percentage error documents the feasibility of the proposed approach in providing accurate speed estimation. Requirement of fewer resources, simplicity of implementation, no significant practical limitations and satisfactory estimation accuracy are the main observed benefits of the proposed method in this work. Fig. 12 shows the RMSE foe each speed category starting from standstill and ending with rated speed. Again, Fig. 12 illustrates that the proposed method offers better speed estimation accuracy in rated speed and less accurate estimation with speed level close to standstill.

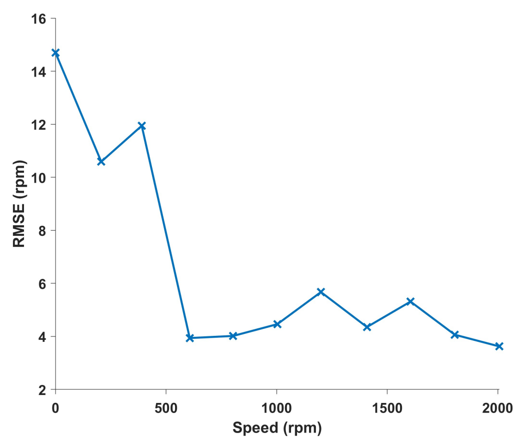


Fig. 12. RMSE distribution over full range motor speed

V. Conclusion

This work proposed new motor speed estimation approach using vibration signal which are generated from the motor rotation. A DC motor have been used to setup the experiment and collect data using vibration sensing devices (accelerometer and gyroscope). Two methods (offline and onboard) have been used to validate the proposed approach and the results shows the success of the proposed new approach in motor speed estimation with high accuracy. The offline method shows the best performance metrics with RMSE of 7.5 rpm and R-Squared value of 0.9998 with percentage error of 0.375%.

The new real-time onboard speed estimation method is successfully proposed and tested with accuracy of 97% using limited hardware resources based on TinyML deep learning regression and classification models.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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TABLE III.
COMPARATIVE ANALYSIS OF THE PROPOSED METHOD

Point of Comparison	Proposed Method	Vibration based method presented in (Induction motor) [18]
Speed Estimation Error		
From zero to full range rpm	0.375%	Estimation of rated speed is conducted.
Rated speed estimation only	0.18%	Up to 0.13%
Methodology of Estimation Requirements		
Description of approach	Six vibrations are incorporated in the analysis (three from accelerometer + three from gyroscope).	Three vibration signals (accelerometer).
Requirement of spectral analysis	No need for spectral analysis.	Needs spectral analysis.
Requirement of a remote computer	Required for model building only.	Required for spectral analysis.

TABLE III.
COMPARATIVE ANALYSIS OF THE PROPOSED METHOD (*Continued*)

Point of Comparison	Proposed Method	Vibration based method presented in (Induction motor) [18]
Real Time Implementation		
Onboard applications	Once model is built, it can be deployed (online) to perform estimation for any speed up to rated speed.	Analysis is performed by obtaining the frequency of rotor speed.
Details of implementation	Requires only the Arduino Nano 33 BLE sense for capturing vibration signals and model deployment.	Smart mobile phone is used for signal capturing.
Limitations		
Constrains on speed estimation	No constrains are reported during the experimental implementation of the proposed speed estimate system.	For induction motors with low number of poles, high synchronous speeds the Nyquist sampling frequency may impose a constrain on the measurement of speed.

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