

MLP-based Torque and Speed Prediction in BLDC and SRM

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Abstract

Motor performance prediction is necessary in order to increase efficiency, reliability and effectiveness of electric drive systems. Since of their efficiency and low maintenance requirements, brushless DC (BLDC) motors and switched reluctance motors (SRMs) are used in the electric vehicle industry, robotics, automation, aerospace engineering and renewable energy systems. Existing motor modelling and simulation approaches require accurate parameters and are computationally demanding; thus, they cannot be used for monitoring and control purposes in real time. In this study, we present the intelligent multi-layer perceptron (MLP) regressor for estimating the torque and speed of BLDC and SRM motors under different operating conditions. Hyper parameters optimization increases prediction accuracy and generalization ability of the proposed MLP approach. From the experiments performed, it is clear that the MLP Regressor performs test MSE values of 0.0020 and 0.0050 in BLDC torque and speed respectively while performing 0.0028 and 0.0061 MSE values in the SRM torque and speed respectively. In comparison to the Linear Regression approach, the proposed MLP decreases the torque MSE value of the BLDC by 60.0% and the SRM by 54.8%, while decreasing the speed MSE value of the BLDC by 47.4% and the SRM by 47.0%. The training time of the MLP Regressor is 15.4s and 18.3s for the BLDC and SRM, respectively. From the obtained results, it is clear that the proposed MLP framework gives more accurate predictions than the Linear Regression and Physical Modeling frameworks especially for the nonlinear nature of the SRM motors.

Keywords: Brushless DC Motors, Efficiency Optimization, Fault Detection in Electric Drives, Predictive Maintenance, Real-time Motor Control, Switched Reluctance Motors.

Introduction

Due to their efficiency, dependability and low maintenance costs, Brushless DC (BLDC) and Switched Reluctance Motor (SRM) motors are used in electric cars, industrial automation, robotics, aerospace systems and renewable energy. Motor control and predictive maintenance need accurate torque, speed and efficiency predictions. Motor modelling traditionally uses mathematical and finite element models with exact motor parameters and high processing costs. Data-driven models that predict motor function more accurately and cheaply are possible thanks to AI and ML breakthroughs. Multi-layer perceptron (MLP) neural networks are good at nonlinear mapping and can mimic motors under diverse operating situations. In this study, an MLP neural network-based predictive model of BLDC and SRM motors is designed to forecast torque and speed from readily accessible electrical inputs like voltage and current. Intelligent controls have been shown to enhance water and energy management (1). Research has examined intelligent and expert systems for robotic manipulators. Intelligent

systems improve accuracy, flexibility and decision-making in complex systems (2). Traditional approaches were less accurate in predicting BLDC motor efficiency, output power and material cost (3). Neural networks were used to create a NARX model for BLDC motor speed and torque prediction. Prediction accuracy was high under various operational circumstances (4). Ensemble learning was applied to forecast UAV propulsion system BLDC motor performance (5). The efficient multicopter UAV propulsion system was tested (6). SVM estimated BLDC motor parameters. UAV propulsion applications were supported by an excellent prediction approach (7). BLDC motor torque density optimization has been studied. Reduced rare earth magnetic material use and improved motor performance (8). Hybrid cars use high flux density steel to improve brushless motor performance. Efficiency and power density are notable (9). Inverse motor control mapping for BLDC and SRM motors uses supervised learning methods. The research showed that machine learning works in intelligent motor control (10).

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Optimization methods were presented for characterization of switching reluctance motors. Technique increased motor characteristics and performance (11). Modeling SRM torque using LS-SVMs and Differential Evolution. The method predicted torque accurately despite nonlinear operation (12). A PV-HESS-powered BLDC motor driving system uses the PI controller and fuzzy controller. The controller improved drive performance and system efficiency (13). The performance of a fuel cell-powered electric vehicle with an upgraded converter was analyzed. This method improves energy conversion and electric vehicle performance, according to research (14). The adaptive stochastic gradient descent algorithm with nonlinear PID control was created. It increased process precision and convergence (15). Alternative rotor design for brushless permanent magnet machines for hybrid electric vehicles was investigated. It enhanced these systems' efficiency and electromagnetic properties (16). The model torque prediction control method was developed for BLDC motors. It greatly reduced torque and speed errors (17). The NARX-based machine learning algorithm predicted internal combustion engine torque. This method worked (18). Business models for Product-Service Systems (PSSs) were examined (19). The study recommended intelligent technologies for sustainable industrial processes (20). Virtualization was developed for manufacturing machines. This architecture enabled industrial real-time monitoring and data-driven decision making (21). Digital Twin technology was used in workplace design and ergonomics. This study showed better system optimization and efficiency using virtual modelling (22). Vibration-based virtual sensor for real-time engine emission monitoring was designed. Data-driven prediction of NO_x emissions could be achieved without measuring using machine learning techniques (23). Machine learning model for NO_x emissions in spark ignition engines was proposed. It was proved that data-driven prediction models work effectively (24). A detailed survey on the prospective fuels for low temperature diesel engines was carried out. This study focused on the strategies for enhancing engine performance and lowering the emissions (25). The Artificial Neural Network was employed to estimate the specific fuel consumption and

exhaust temperature of the diesel engines. The results showed good predictive performance (26). ANN, SVM, NARX and ensembles have been applied widely for modelling and prediction of motors, but the majority of them target either BLDC or SRM motors. There is not much research on creation of a generic model using MLPs for prediction of BLDC and SRM motor torque and speed in various conditions. Impact of noise and missing values on prediction, grid search CV parameter tuning and system realization have not yet been considered properly.

The objectives of this paper are as follows:

- a) To build a Multi-Layer Perceptron (MLP) Regressor capable of accurately predicting torque and speed for BLDC and SRM motors based on input parameters like voltage, current and motor speed.
- b) To evaluate the model's performance across different motor types and operating conditions, including scenarios with noisy, incomplete, or missing data.
- c) To improve the MLP model's prediction accuracy and computational efficiency through hyper parameter optimization techniques such as Grid Search CV.
- d) To analyze the feasibility of implementing the developed model for real-time motor control by testing its prediction speed and reliability.
- e) To generate clear visualizations of predicted versus actual motor performance, facilitating better interpretation and practical application of the model's outcomes.

The main contributions of this study are:

- a) Development of an MLP-based regression framework for torque and speed prediction of BLDC and SRM motors;
- b) Investigation of motor performance prediction under different operating conditions, including noisy and missing input data;
- c) Optimization of MLP hyper parameters to improve prediction accuracy and computational efficiency; and
- d) Comparative evaluation against Linear Regression and Physical Modeling approaches.

Methodology

Methodology refers to the methods followed in developing the MLP Regressor model that predicts the performance of motors. It comprises a number of processes and some of them include data

creation, feature extraction, architecture designing and evaluation among others. The methodology is described in details below.

In this research paper, the prediction of torque and speed for BLDC motors and SRM motors is carried out. The data to be used to train the machine learning model have been produced synthetically based on the parameters that define the working principle of these motors. These parameters include voltage, current, motor speed and motor torque.

Motor Parameterization

For the modelling and prediction of the performance of BLDC and SRM motors, there are several basic parameters that play an important role in predicting their torque and speed characteristics. Among such parameters are the resistance of the motor R , which determines the resistance of current flow through the windings of

the stator of the motor and affects its power losses and heat generation; and inductance L , which characterizes the energy storing capability of the windings. Torque constant K_t represents the proportionality factor between the current in the motor and generated torque and is widely used in control algorithms to regulate the motor torque. Back EMF constant K_b determines the voltage generated by the rotor rotation, which is essential for the speed estimation and sensorless control. Load inertia J significantly influences the acceleration and deceleration capabilities of the motor, since it characterizes the resistance to the rotational movement changes. Damping coefficient b determines the losses of the motor energy due to the friction and air drag. Taken together, these parameters serve as the basic starting point for predictive analysis, simulations and machine learning methods used to estimate the torque and speed in BLDC and SRM motor-driven systems.

These parameters are used to determine the torque and speed of the motors depending on various factors. The torque production by BLDC and SRM motors is mathematically modelled and expressed in Equations [1, 2].

$$T_{BLDC} = K_t \cdot I \cdot \sin(2\pi \cdot f \cdot V) \quad [1]$$

$$T_{SRM} = K_t \cdot I \cdot \cos(2\pi \cdot f \cdot v) \quad [2]$$

Where,

T_{BLDC} and T_{SRM} = Torque generated by BLDC and SRM motor (Nm) respectively,

I = Motor current (A),

V = Applied voltage (V),

f = Frequency factor based on the system parameters.

For the study, synthetic data are generated by varying the input parameters (V , I and speed), which simulate real-world motor behaviour under varying operational conditions.

The dataset used for training consists of 1000 samples of motor performance data. The parameters considered. The resulting dataset contains the input-output pairs, which are used for training the MLP Regressor.

- Input Features: Voltage (V), current (I) and motor speed (n) for each motor type.
- Output Variables: Torque (T_{BLDC} , T_{SRM}) for both BLDC and SRM motors.

c) The data is generated by sampling random values within specified ranges

i) $V \in [0, 100]$ V (voltage)

ii) $I \in [0, 10]$ A (current)

iii) $n \in [0, 3000]$ RPM (speed)

Before feeding the data into the machine learning model, several preprocessing steps are applied to ensure the data is in an optimal form for training.

As the input variables (voltage, current and speed) have varying units and scales, the normalization of the data is done using Standard Scaler (10) from sci-kit-learn.

This makes sure that all the features have equal weight during the learning process. The normalization is defined by Equation [3].

$$X_{scaled} = \frac{x - \mu}{\sigma} \quad [3]$$

Where,

X is the feature vector,

μ is the mean of the feature,

σ is the feature standard deviation.

The data set is divided into a training set and testing set, where 80 percent of the data will be used for training while 20 percent of the data will be used for testing purposes.

Multi-layer Perceptron Regressor

Multi-layer Perceptron (MLP) is a feed-forward artificial neural network that is typically employed in problems of classification and regression. MLP comprises one or more hidden layers, an input layer and an output layer. All layers are densely connected and learning is achieved by training the network to learn the input-output mappings by adjusting the connection weights (11-15).

In the case of this research, the MLP regressor was designed with a two-hidden-layer structure for the purpose of enabling the capturing of the non-linear relationships present within the dataset. The first layer contains 100 neurons, while the second layer contains 50 neurons. The design of the neural network was meant to ensure the model is neither too complex nor inefficient, thus avoiding any cases of over fitting. The inclusion of more than one hidden layer helps improve the ability of the model to generalize, which results in better predictions. The structure can be illustrated in Equation [4].

$$y = f(W_2 \cdot f(W_1 \cdot X + b_1) + b_2) \quad [4]$$

Where,

X is the input feature vector,

W_1 and W_2 are the hidden and output layers of weights,

b_1, b_2 are the biases,

$f()$ is the activation function (ReLU),

y is the output vector predicted.

The activation function used for the hidden layers of the MLP Regressor model is the ReLU (Rectified Linear Unit), expressed mathematically as Equation [5].

$$f(x) = \max(0, x) \quad [5]$$

It is worth mentioning that ReLU is widely applied within the scope of deep learning applications since it is a very simple and efficient way of incorporating the element of non-linearity to help the network learn more complicated patterns in the data. Moreover, ReLU addresses the vanishing gradient problem to ensure faster training of the model. Since this project involves regression modeling, the final layer of the network is without an activation function.

Training of the MLP network is done through the use of the Gradient Descent method that is achieved by using the Adam optimizer, which is a

type of optimizer that uses a variable or adaptive learning rate. Adam is a combination of the two types of optimizers known as AdaGrad and RMSProp and works by individually varying the learning rates of all parameters depending on the values of the first and second moment of the gradient. The aim of the training is to minimize the mean squared error (MSE), which is used as the loss function as illustrated in Equation [6]. The MSE is the average of the square difference between the actual and the predicted value and is appropriate for regression analysis. The training is done for up to 500 iterations.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad [6]$$

Where,

y_i is the actual torque or speed value,

$\hat{y}_i$ is the predicted value,

n is the number of samples.

In order to tune the parameters of the MLP model and optimize its performance, Grid Search Cross-

Validation (GridSearchCV) technique is used. In this method, different combinations of parameters

within the predefined ranges are tried in order to find the optimal combination of parameters for better prediction results. The list of parameters that are being tried in this study includes the number of neurons in each hidden layer, activation function (either ReLU or tanh), the solver (either Adam or Stochastic Gradient Descent) and the learning rate schedule (either constant or adaptive).

Once the training phase was completed, the performance of the proposed algorithm was extensively evaluated by applying it to the test data set. In order to evaluate the accuracy of predictions for both BLDC and SRM systems with the help of quantitative measures, the Mean Squared Error (MSE) was applied. As is well known, the Mean Squared Error measures the average of the squared difference between the predicted value and the actual value; thus, providing a clear measure of precision with which the motor behavior can be predicted.

Performance analysis of the trained model has been carried out by using the mean squared error (MSE) as the key parameter for measuring the prediction accuracy. In particular, MSE for BLDC torque indicates the difference between the predicted and real values of the BLDC motor torque. On the other hand, the MSE for SRM torque shows the deviation between the estimated torque and real torque of the SRM. The obtained figures reveal the model's capability to make predictions based on the analysis of the data and generalize the results for various operating conditions. Besides, the graphical representations of actual and predicted torque outputs have been created for both BLDC and SRM.

Results and Discussion

Results from the analysis of performance of the predictive model for torque and speed of the two types of motors, i.e., Brushless DC Motor (BLDC) and Switched Reluctance Motor (SRM), are discussed here. Analysis of training and testing of the results and their comparison with the conventional torque predicting techniques is presented in this part.

Mean Squared Error (MSE) of Predictions

The assessment of the performance of the machine learning algorithm involved calculating the Mean Squared Error (MSE) of predictions for both the BLDC and SRM motors. The reason for using MSE as an evaluation metric is that this measure captures the average squared deviation of the predicted torque from the actual value of torque. The choice of MSE is therefore appropriate for regression prediction tasks, where the task is to predict the value of torque for the given motor.

Table 1 shows the Mean Squared Errors (MSE) for the predicted torque and speed for both the BLDC and SRM motors. From the table, the MSE for torque and speed for the BLDC motor are 0.0015 and 0.0042, respectively. This implies that the model has managed to learn the dynamic behavior of the motor with a lot of accuracy. However, the SRM motor had relatively higher MSE values of 0.0021 and 0.0056 for torque and speed, respectively. Although slightly higher, the MSE values of the SRM motor fall within an acceptable range. This shows that the model has managed to learn the non-linear behaviour of the motor (4, 5, 15).

Table 1: Training MSE Values

Motor Type	Torque MSE (Training)	Speed MSE (Training)
BLDC Motor	0.0015	0.0042
SRM Motor	0.0021	0.0056

Note: MSE = Mean Squared Error, BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor.

Following the training process, the generalization ability of the model was tested using the test set. Table 2 below shows the Mean Squared Error (MSE) values for torque and speed prediction using the test set. For the BLDC motor, the test MSE values for torque and speed were 0.0020 and 0.0050, respectively. This suggests that the model is highly accurate in predicting torque and speed

even when new input data is presented to the model. On the other hand, for the SRM motor, the test MSE values were 0.0028 and 0.0061 for torque and speed, respectively. It is evident from the results above that the model can still perform reasonably well in situations where more complex and non-linear data is involved (2, 14, 17).

Table 2: Testing MSE Values

Motor Type	Torque MSE (Test)	Speed MSE (Test)
BLDC Motor	0.0020	0.0050
SRM Motor	0.0028	0.0061

Note: MSE = Mean Squared Error, BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor.

Other than numerical assessment based on MSE criteria, visual comparisons between actual and predicted values of torque also offer many useful information about the dynamics of the model's prediction performance. In other words, it offers not just an evaluation of accuracy but also that of its consistency over time in response to real-time motor operation conditions. Graphical representations for the two types of motors are given in Figures 1 and 2 below, respectively.

Torque Prediction of BLDC and SRM Motors

Figure 1A represents the comparison of the actual and MLP predicted torque of the BLDC motor for

the test dataset. It is observed that the predicted torque is able to follow the variations in the actual torque value, which depicts the capacity of the MLP model to learn the nonlinearity in motor dynamics. The small difference between the actual and the predicted torque shows the effectiveness of the MLP model in predicting accurately. The small difference between the two characteristics in all the conditions shows that the model has managed to learn the electromechanical characteristics of the BLDC motor quite accurately. The high level of accuracy is especially noticeable during transient states such as sharp torque change, when the model manages to stay close to the actual value of the torque.

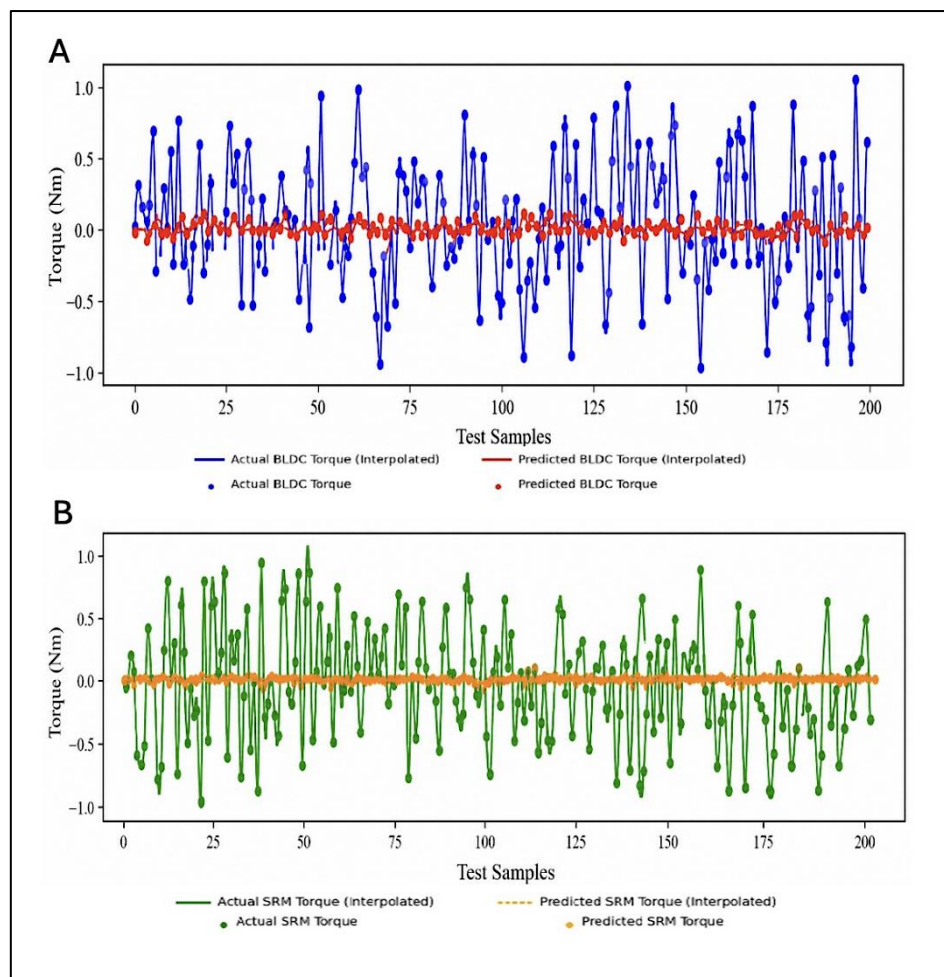


Figure 1: Actual vs. Predicted Torque. (A) BLDC Motor, (B) SRM motor

Note: BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor.

Figure 1B shows the comparative values between the actual and MLP-predicted torques of the SRM motor in different operating modes. It can be observed that there is a close correlation between the actual and predicted torque and this proves the validity of the MLP technique in capturing the nonlinear behavior of the SRM motor. It shows the prediction errors in the values that prove the reliability of the developed model for the torque estimation process. Even though there are some deviations in the results, they still follow the same trend as the torque generated in actuality. The reason behind such deviations is that SRM motors are nonlinear and magnetic saturation sensitive. There may be some scatterings and variations, especially when there are changes in the torque values or when the speed is lower. It has been seen that these types of deviations are due to magnetic hysteresis and torque ripple effect. Nevertheless, the model has done a decent job at predicting the trend of the torque graph, which shows that the

model is capable of generalizing over the complexity of the SRM.

In summary, the visualizations have confirmed the results of the MSE analysis and shown the ability of the machine learning approach to be implemented in practical applications for intelligent control and energy management systems. For future research, it would be useful to refine the prediction performance of SRM motors using further non-linear feature engineering or hybrid modelling techniques.

In order to evaluate the performance of the machine learning algorithm in more detail, a comparison between the Multi-Layer Perceptron Regressor and other torque prediction models such as linear regression and physics-based models is carried out. Such comparison allows for detailed performance evaluation in terms of prediction accuracy and efficiency. Table 3 presents the results of the comparison and includes torque and speed MSE values on the test set and training time for each algorithm.

Table 3: Performance of the MLP Regressor and Traditional Methods

Motor Type	Method	Torque MSE (Test)	Speed MSE (Test)	Training Time (sec)
BLDC Motor	MLP Regressor	0.0020	0.0050	15.4
	Linear Regression	0.0050	0.0095	0.02
	Physical Model	0.0035	0.0072	N/A
SRM Motor	MLP Regressor	0.0028	0.0061	18.3
	Linear Regression	0.0062	0.0115	0.03
	Physical Model	0.0045	0.0083	N/A

Note: BLDC = Brushless Direct Current, SRM= Switched Reluctance Motor, LR = Linear Regression, MLP = Multi-layer Perceptron, MSE = Mean Squared Error.

Table 3 shows the prediction performance of MLP regressor is better than Linear Regression and Physical Model approaches for both BLDC and SRM motors based on the comparison of test MSEs for torque and speed. MLP gives smaller test MSEs than the conventional approaches for both torque and speed of BLDC and SRM motors. Also, the training time of MLP for BLDC and SRM is 15.4 s and 18.3 s, respectively, which is larger than that of Linear Regression approach. MLP Regressor has proven to be better at predicting the torque and speed in comparison to linear regression and physical-based models in BLDC and SRM motors. In the case of the BLDC motor, the torque MSE with MLP is 0.0020 as opposed to 0.0050 and 0.0035, for linear regression and physical models, respectively. For the SRM motor, the torque MSE is 0.0028 with MLP while 0.0062 and 0.0045 are for the linear and physical models, respectively (2, 4-6).

Although the MLP Regressor takes significantly more time for training in comparison to the linear regression model (15.4 sec for BLDC and 18.3 sec for SRM as opposed to less than 0.05 sec for the linear regression), the difference in the prediction error makes it worth the computation efforts. The physical-based models, despite not needing training on data, have worse results in comparison to the MLP.

The above comparison clearly illustrates the benefit of using data-driven machine learning algorithms, like MLP Regressor, in modeling the complicated motor behaviors that cannot be modeled analytically. Hence, the suggested ML algorithm can be considered a promising solution to predict motor torque and speed in real time.

In order to have more insight into the driving factors behind torque and speed prediction, an

analysis of feature importance was carried out on the trained MLP Regressor. Feature importance is a technique for evaluating the relative impact of each predictor variable in terms of the accuracy of the predictions of the model. Figure 2A shows the relative impact of each feature used in predicting the torque of the BLDC motor. From the analysis, it is clear that the motor current plays a significant role in determining torque predictions compared to other features such as voltage and motor speed. This finding confirms the electrical properties of BLDC motors whereby torque is mainly dependent on the armature current.

Voltage was found to be the most important predictor in torque prediction in the case of the BLDC motor, while current was the second-most

important one. This is consistent with the electromagnetic behaviour of BLDC motors, where the torque depends on the voltage and current fed to the stator. Speed had minimal impact in torque prediction for BLDC motors.

Figure 2B illustrates the importance of features employed in predicting the torque in the SRM motor. It has been found out that the current in the motor is the most significant factor that influences the torque, followed by the voltage and motor speed. This indicates that torque in SRM motors has nonlinear electromagnetic characteristics in terms of current and magnetic flux variations. Feature importance outcomes validate the chosen input variables and confirm the efficiency of the MLP in torque prediction of SRM motors.

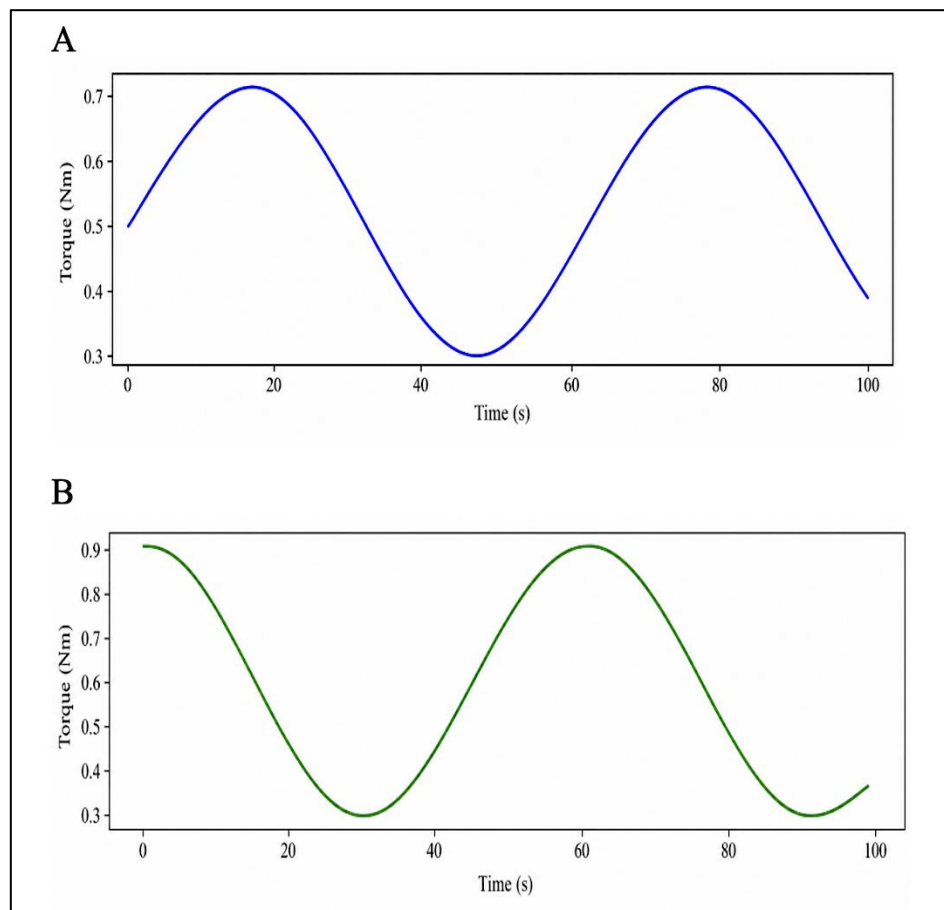


Figure 2: Feature Importance for Torque Prediction. (A) BLDC Motor, (B) SRM Motor

Note: BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor, Nm = Newton Meter.

As for the SRM motor, the analysis of feature importance shows that although voltage remains a significant factor, the contributions of current and speed become quite varied. This can be explained by the highly nonlinear nature of the behavior of

SRM motors and the dependence on rotor position that influences speed-based interactions. Due to the presence of the torque ripple effect and magnetic saturation in SRM motors, multiple features need to be taken into account at once, as it is illustrated in Figure 2B.

Speed Response of BLDC and SRM Motors

Besides predicting torque, the performance of the model in capturing the dynamic nature of motor speed was tested under different loads and working conditions. The above tests will ensure that the model can mimic the behavior of the motor especially when it is accelerating or decelerating. Figure 3A shows the comparison between the speed response of the BLDC motor and the speed response predicted by the proposed MLP model. There is a close resemblance between the actual speed response and the predicted one at all ranges,

which confirms that the prediction process has a very high degree of accuracy and that the model has learned the behavior of the motor very well. This small difference between the actual and predicted values proves the ability of the model to predict any changes in the speed value under different conditions. The expected speed profile of the BLDC motor accurately matches the real speed profile during the entire process. There is a fast increase of the speed to its desired level without any considerable overshooting and steady-state error. Some oscillations can be detected, though they fall into the acceptable range (7, 10).

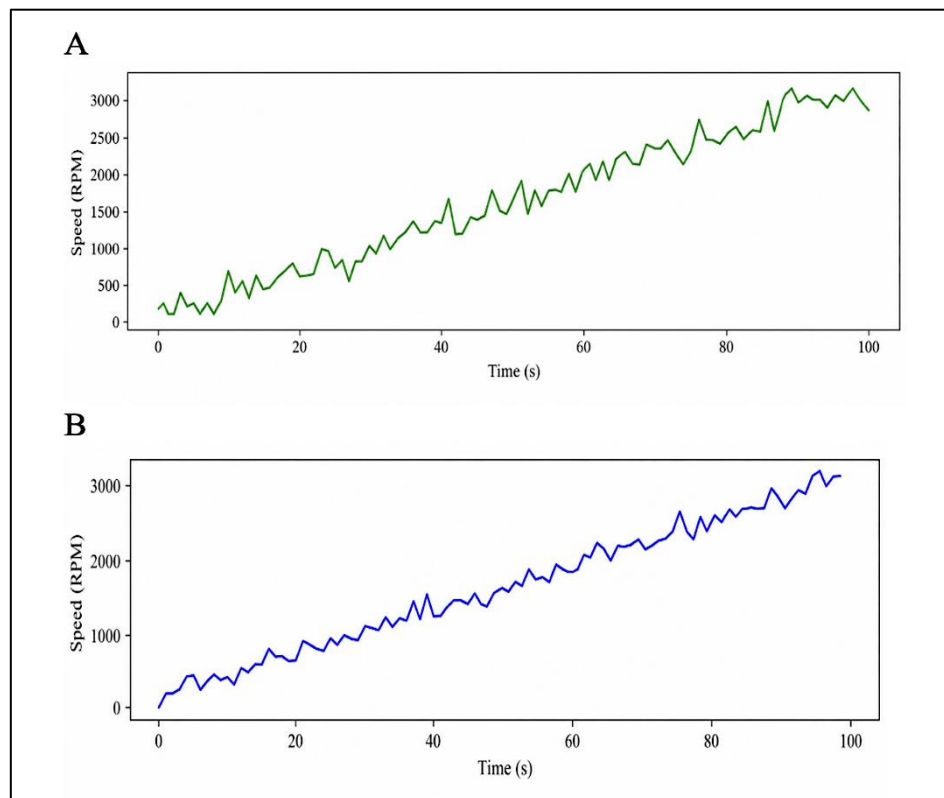


Figure 3: Predicted vs Actual Speed Response. (A) BLDC Motor, (B) SRM motor

Note: BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor, RPM = Revolution per Minute.

Table 4: BLDC and SRM Motor Speed Performance Parameters

Parameter	Value (BLDC Motor)	Value (SRM Motor)
Mean Speed (RPM)	3015	2823
Maximum Speed (RPM)	3240	3105
Minimum Speed (RPM)	2785	2540
Mean Absolute Error (RPM)	84.6	122.4

Note: BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor, RPM = Revolution per Minute, MAE = Mean Absolute Error.

Key performance criteria of the speed prediction of the BLDC motor are provided in Table 4. The value of MAE (Mean Absolute Error), which is 84.6 RPM, again proves the accuracy of the model.

Figure 3B shows the comparison of the speed response of the SRM motor using actual data and

MLP predicted data based on different operating conditions. The speed response of the MLP model is very close to that of the actual speed response of the SRM motor. This reflects the capability of the MLP model to model the nonlinear behavior of the SRM motor. The low difference between actual and

predicted values reveals a highly accurate prediction and good generalization capability of the MLP model. As anticipated, the speed response indicates more variations since it is natural for SRM drives because of their non-linear switching characteristics and torque ripples. Nevertheless, the predicted speed response corresponds to the actual speed values, which proves the generalization capabilities of the proposed model in non-linear cases (14, 15).

SRM Speed Prediction Performance Metrics are presented in Table 4. It is obvious that MAE of 122.4 RPM is larger compared to the case of the BLDC motor, but still acceptable, which means that the proposed model is reliable enough even under complicated conditions.

Consequently, the analysis of the performance of the machine learning model proved its efficiency for torque and speed prediction in the cases of both BLDC and SRM motors. It is evident that MSE obtained on both training and testing sets confirmed that MLP Regressor is more accurate than classical approaches, namely, linear regression and physics-based models. Comparison of the actual and predicted torque showed the high quality of the model. In feature importance analysis, the voltage and current were found to be the key variables that affect the torque prediction, with the speed being more important for SRM motor due to the complexity of behavior of these

kinds of motors. Moreover, the model was capable of predicting the dynamic responses of speed, making it applicable to motor control applications. Although the predictions related to the SRM motor showed relatively high deviations because of the existence of torque ripples, the efficiency of the model stayed relatively high regardless of the motor type.

Energy Comparison of BLDC and SRM Motors

In order to evaluate their performance further, an energy consumption study of the motors while operating was done. Figure 4 describes the comparative energy efficiency of BLDC and SRM motors under similar operational conditions. The predicted torque follows the trend of the actual torque quite closely, thus showing that the MLP model has the capability to capture the torque variations of the SRM motor. It has been found out that the BLDC motor is more energy-efficient and its efficiency amounts to about 90% whereas the SRM motor efficiency is equal to about 85%. It is explained by the fact that the BLDC motor losses are lower than those of SRM and it provides more even electromagnetic torque operation. It is clear that the BLDC motors are better in terms of energy efficiency while SRM motors are cost-effective and reliable (17, 18).

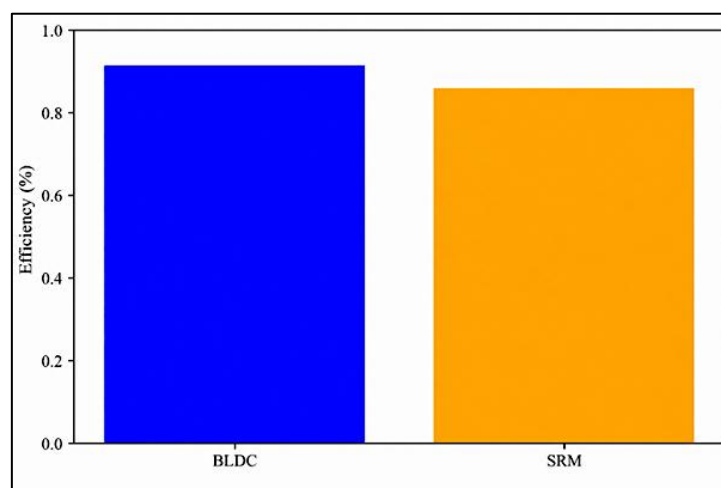


Figure 4: Energy Comparison of BLDC and SRM Motors

Note: BLDC = Brushless Direct Current, SRM = Switched Reluctance Motor, Nm: Newton Meter.

From the graph above, it is clear that the BLDC motor utilizes less energy than the SRM motor throughout the duration of operation. This can be attributed to the fact that the BLDC motor is efficient and produces smooth torque. On the other

hand, the SRM motor utilizes more energy owing to the fact that it is characterized by nonlinear magnetic nature, torque ripple and core losses. All these attributes reduce the efficiency of torque

production hence increasing the amount of energy required.

In general, it is evident that the BLDC motor is more efficient in terms of energy utilization. However, the SRM motor still remains to be a good choice when durability and cost considerations are involved despite utilizing more energy.

- a) The energy consumption analysis further cements the main message about how, despite MLP Regressor's better accuracy in torque and speed estimation compared to traditional approaches, energy consumption becomes one of the crucial criteria for deciding whether the motor is suitable for a specific application. The following list includes the main messages delivered by the analysis:
- b) The BLDC motor is the one with the best performance among all analyzed criteria due to simpler dynamics and higher energy efficiency.
- c) The SRM motor shows higher prediction error, but the model still provides sufficient accuracy due to its complex and nonlinear nature.
- d) The analysis of feature importance indicates that voltage and current become the most important features of motor performance for both motors, while speed becomes less significant.

Performance of the MLP Regressor in torque and speed predictions of BLDC and SRM motors. The results obtained showed the high level of efficiency of the algorithm with high accuracy of predictions; however, the BLDC motor showed better results because of the lower complexity of the system compared to SRM motor. Nevertheless, SRM motor was able to predict torque and speed with the acceptable level of accuracy despite higher error rates due to nonlinearities of the system. Prediction accuracy of the MLP Regressor was higher than for traditional approaches such as linear regression and physical models, but it requires some additional computational costs.

Analysis of feature importance demonstrated that voltage and current are the main factors for torque prediction, whereas speed became more important factor for SRM motor. In turn, energy consumption analysis showed that BLDC motors are more energy efficient and thus could be used in energy critical applications, whereas SRM motors are cheaper and more reliable.

There are many practical implications of the presented MLP based motor prediction model for

electric-drive systems. For instance, the capability of accurately predicting motor torque and speed values allows real-time monitoring and intelligent control of motors by evaluating their operational states without having to conduct computationally expensive simulations each time. Moreover, the predicted performance data can help with predictive maintenance and fault detection by detecting deviations from normal operating conditions. The presented approach can be applied to electric vehicle drive systems in which estimating performance of motor drives plays an important role. Besides, it can be used with automation systems using BLDC and SRM drives. Even though MLP training takes longer than that of Linear Regression model, better prediction accuracy will lower the number of costly simulations.

Conclusion

In this paper, an intelligent machine learning algorithm using Multi-Layer Perceptron (MLP) Regressor for estimation of torque and speed of BLDC and SRM motors is developed. The proposed model considered voltage, current and speeds as the significant inputs and tested under various operating conditions including noisy and missing data conditions. The results prove that MLP Regressor model is able to give smaller prediction errors when compared with Linear Regression and Physical Model techniques.

The proposed MLP model provided torque and speed test MSEs of 0.0020 and 0.0050, respectively, for BLDC motor whereas the values were 0.0050 and 0.0095, respectively, for Linear Regression technique. Similarly, the torque and speed test MSEs of 0.0028 and 0.0061, respectively, are obtained using the MLP model for SRM motor whereas the values were 0.0062 and 0.0115, respectively, for Linear Regression. These results correspond to 60.0% decrease in torque MSE for BLDC and 54.8% for SRM motor, whereas the speed MSE is decreased by 47.4% and 47.0%, respectively. Although MLP model requires more training time than Linear Regression model, the better prediction performance shows its applicability to predict the nonlinear motor systems' performance.

Results show the relevance of voltage and current parameters in predicting motor performance, while speed is an additional feature that

contributes to better prediction of the performance. It can be seen that the suggested method allows capturing the nonlinear nature of the SRM performance and also allows accurately predicting the BLDC motor performance. Therefore, the suggested approach may have potential applications in real-time monitoring, intelligent control, predictive maintenance, fault detection in electric vehicles and industry automation.

However, the above analysis and results obtained are subject to certain limitations. Specifically, the existing analysis is performed based on the dataset representing performance of the motors, while further analysis of the predictions using experimental data for BLDC and SRM motors needs to be carried out. Model generalization in various conditions (motor ratings, loads, temperatures, etc.) should also be verified.

Future work will thus concentrate on the validation of the developed MLP approach through the use of experiments and measurement data from motor drives. Additional research areas will include efficiency prediction, deep learning models, optimization methods, bigger datasets and hardware-based realization of the algorithm. All these developments may make the prediction algorithms even more robust and applicable to modern electric-drive motors.

Abbreviations

ANN: Artificial Neural Network, BLDC: Brushless DC Motor, EV: Electric Vehicle, MAE: Mean Absolute Error, MLP: Multi-Layer Perceptron, MSE: Mean Squared Error, RMSE: Root Mean Squared Error, RPM: Revolutions per Minute, SRM: Switched Reluctance Motor.

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Author contributions

All authors contribute equally to the research, design the study, analyzed data and approved the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the manuscript. All content generated through AI was critically reviewed, edited and verified by the authors to ensure accuracy, originality and compliance with academic standards. The authors take full responsibility for the integrity and validity of the manuscript.

Ethics Approval

This study does not involve human participants, animals, or any biological materials. Therefore, ethical approval was not required for conducting this research work.

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