A Development and Implementation of PMSM Torque Estimation Based on Machine Learning Techniques

Wannadear Nawae and Kittikhun Thongpull*
Department of Electrical Engineering, Faculty of Engineering,
Prince of Songkla University, Songkhla, Thailand

Abstract: Nowadays, robotic arms are commonly used in industrial medical, and home service applications. For safety reasons, it is vital to aware their operating conditions such as speed, position, and torque which result in the need of delegate sensors with extra cost, bulky mechanical installation, and advanced data acquisition electronics. In contrast to using actual sensors, in this paper we present a development of sensorless torque estimation based on machine learning technique for Permanent Magnet Synchronous Motors (PMSM) focusing to serve safety required applications e.g., robotic arm. The proposed architecture comprises of the estimation model generation process and a motor test bench to facilitate and accelerate the implementation procedures. Three statistical based machine learning methods have been applied in this work including Neural Networks regression, Linear regression, and Stepwise regression. The estimation performance has been validated by comparing the estimated results with ground truths from an actual torque sensor. The estimation model based on Neural Networks regression has achieved highest accuracy at 0.6792 of RMSE and 0.9908 of R value. In addition, we investigated the realization of an application by using the proposed torque estimation technique in the simulated robotic arm collision detection experiment. The results show that the proposed torque estimation technique has efficacy to adapt in such use case with the detection error below 22.38%.

Keywords **—**PMSM, Torque estimation, Sensorless torque measurement, Machine learning, Regression.

I. INTRODUCTION

Recently robotic arm/manipulator applications tend to be human-oriented operations, e.g., home-use [1],[2] medical [3], and manufacturing [4]. To choose an appropriate robotic arm, various parameters should be considered such as operating space, degree of freedom, robot geometry, load size and weight, movement speed, and rated torque. More importantly, safety features are necessary for every robot to guarantee no accident in operations, especially for those that interact or contact with human operators or users. Hence, advanced sensors, i.e., magnetic absolute encoder, and torque transducer are commonly employed to obtain information that are needed in algorithms for safety condition awareness of the robot. However, delicate sensors are in exchange for cost, size, power consumption etc. These gain interest in research for sensorless techniques developed to obtain operating conditions of robot actuators i.e., motors, completely based on electrical signals or back-electromotive force (back-EMF) from the motor itself without using an actual or physical attached sensor. Typically, a Permanent Magnet Synchronous Motor (PMSM) is controlled by energizing two of its three winding phases while one phase winding is not conducted and left floating creating back-EMF signals related to the motor operating activities [5]. The employing sensorless technique for speed and position control is presented in [6], better speed versus torque characteristics, high dynamic response, and zero electrical wear have been achieved, however, torque information was not investigated. The Electromagnetic Torque [7] is a deterministic mathematical calculation to determine motor torque based on back-EMF signals however the consistency of estimated torque relies heavily on accurate value of motor parameters. In contrast, capturing back-EMF signals and analyze with machine learning methods for regression can be exploited to estimate motor speed and torque [8] based on learned statistical information without the need for motor parameters knowledge. Thus, in this paper, we present the development of PMSM torque estimation technique based on machine learning for regression and the architecture for creating estimation models. We have developed a motor test bench to facilitate the model learning procedure also to evaluate the generated models. The proposed software system has been developed in MATLAB Simulink and tested on actual hardware with its own developed test platform. Two experiments were conducted to evaluate the performance of

The manuscript received January 9,2021; revised February 9, 2021; accepted March 27, 2021. Date of publication June 30, 2021.

*Corresponding author: Kittikhun Thongpull, Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla, Thailand. (E-mail: kittikhun.t@psu.ac.th).

the generated estimation models from the proposed architecture in the continuous torque measurement experiment and the usefulness of applying the estimation model in an application in the simulated robotic arm collision detection.

II. PMSM Torque Estimation

A. *Sensorless PMSM control*

Permanent magnet synchronous motors (PMSM) require advanced control processes to achieve desired operations. One of the commonly used PMSM control methods is Field-Oriented Control (FOC) [9], [10] as its capability to provide motor rotation efficiency and maximum torque. FOC requires a number of parameters such as rotor position, and speed of the motor for its driving procedures. This information can be obtained by attaching a sensor at the motor shaft which adds system complexity cost and size while analyzing Back-EMF signals of the motor is a common alternative that can provide similar information. Conventionally, FOC motor control process uses only the rotor position or rotor angle (Theta) for switching pattern generation (SVM) providing to the PWM driver as described in Fig. 1. However, Back-EMF also has a significant relation to motor speed and torque which can be quantified by using mathematical calculations without using actual sensors [7]. Thus, in this work, we exploit the relation between motor torque and Back-EMF signal to estimate torque without using actual sensor based on a statistical analysis of Back-EMF signal and machine learning.

B. *Sensorless PMSM Torque estimation*

As stated earlier, the PMSM operation generates electromagnetic induction of magnetic fields that can be analyzed deterministically by Electromagnetic Torque equation [7], nevertheless uncertain motor parameters and the motor usage behavior such as operating time, current and temperature result in errors. In addition, estimating

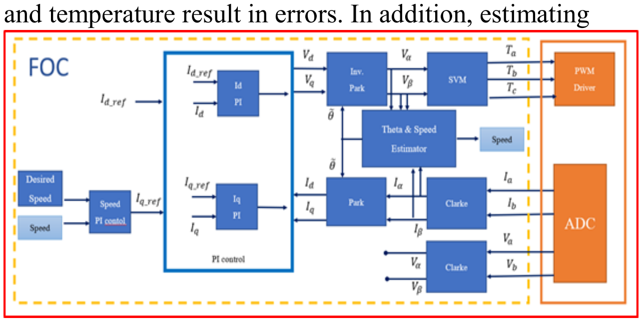


Fig. 1. PMSM control diagram

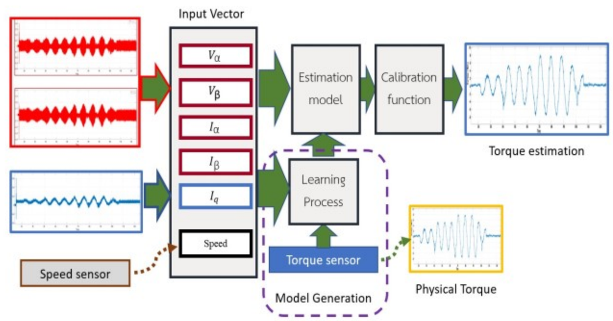


Fig. 2 Machine learning process

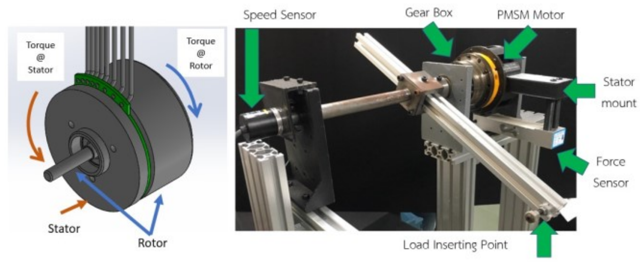


Fig. 3 Torque measurement;
Torque of motor(Left) and Low-cost motor test bench(Right)

motor torque can also be achieved by using statistical models of recorded Back-EMF signals and related motor operating conditions. By this technique, a number of motor parameters can be omitted for torque estimation resulting in a less parameter-dependent performance of the estimation process. To obtain the estimation models in this work, machine learning [11] approach is employed. Three models were selected with different complexity. Linear regression (LR) [12], Stepwise regression (SR) [13], and Neural Networks (NNS) regression [14] are chosen as estimation models in this work. The models are generated from the learning process (training) that takes the input information of previously recorded Back-EMF signals and motor operational conditions formulated as the input vector of the estimation model. The proposed input vector comprises of six features including current sampling (Iα and Iβ) and voltage sampling (Vα and Vβ) both are the result of Clarke transformation and Park transformation of current (Iq) and the rotational speed at the output shaft. The learning process adjusts model properties by the relation between the input vector and output target vector which is reference torque derived from a physical sensor. Fig. 2 illustrates the proposed machine learning process of torque estimation model generation. The output vector usually is normalized thus a calibration function is required.

C. *Motor Testbench*

$$\tau_{Stator} = \tau_{Rotor} \qquad (1)$$

The structure of proposed machine learning based PMSM torque estimation requires reference torque information for training procedure. An actual torque transducer is attached to the motor directly to measure the torque applied on the motor rotor during the data collection process. To facilitate the training procedure, we developed a low-cost motor testbench that supports the data collection of a motor with actual load condition to simulate the real operation situation. Fig.3(right) illustrates the implemented motor testbench consists of a PMSM under the test with gearbox, output shaft and load inserting point, force sensor at motor stator, and speed sensor. The motor torque is acquired from the load cell sensor installed at the motor stationary part which is the torque applied at the motor stator. The motor rotor torque can be calculated by the principle of rotor-

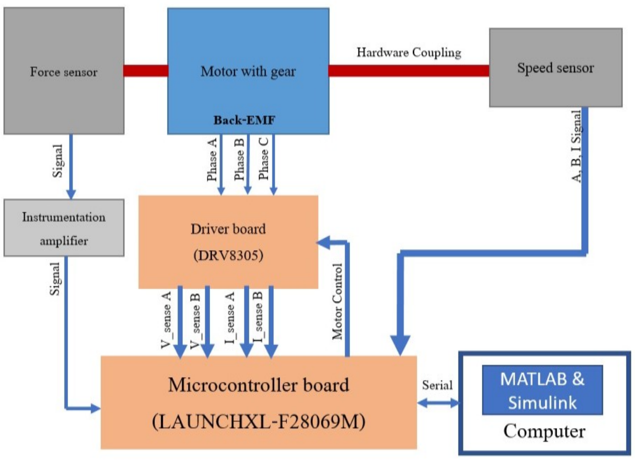


Fig. 4 Schematic diagram of low-cost motor test bench

stator torque relation as shown in eq.1 described in [15] that the force applied at the stationary part of the motor is equal to the rotor part of the motor as demonstrated in Fig.3(left).

The motor under the test is controlled by a motor driver during the data collection process. The specifications of the motor are given in Table 4. The motor driver is used to acquire Back-EMF signal as well as sensor data, i.e. force, shaft speed and position. A stain gate is used to measure the torque applied at the motor stator. A speed sensor is coupled at the output shaft of the gearbox. Fig. 4 depicts the electrical block diagram of the implemented motor test bench. A Microcontroller TMS320F28069[16] and Motor driver DRV8305[17] are occupied to control the motor under the test. We implemented the data collection and training process for creating torque estimation models on MATLAB Simulink. The training process employs Regression Learner toolbox [18] to generate estimation models with a choice of regression techniques. In this work, Linear regression and Stepwise regression are chosen. The Neural Networks based estimation model is learned from the Neural Networks time series toolbox [19]. In this work, we constrained the choice of regression models by the capability of implementation on actual hardware. A trained regression model for torque estimation is integrated into the motor control process developed on MATLAB Simulink using Texas Instrument C2000 support from embedded coder [20], thus, the generated torque estimation model can perform simultaneously on the motor driver microcontroller in real-time.

III. Experiment and Result

A. Experiment setup

We performed two experiment scenarios including continuous torque measurement and simulated robotic arm collision detection both performed using the implemented motor testbench cooperated with the proposed machine learning process of torque estimation model generation. The continuous torque measurement is to observe the performance of generated torque estimation models referring to an actual torque sensor. The simulated robotic arm collision mimics a use case by adapting the robotic arm application for collision detection [21]. Three machine learning models were used in the proposed machine learning process consisting of Linear regression, Stepwise regression, and Neural Networks. The recorded data for the learning process of estimation model generation was divided using sample holdout method into 80:20 ratios for train and test procedure respectively. The motor under the test was controlled at three constant speeds: 700, 1000 and 1200 rpm.

B. Continuous torque measurement

In this experiment scenario, we study the efficacy of the generated estimation model for measuring torque in a continuous rotation period at a constant speed by comparing the estimation result to an actual torque sensor. Fig.5 illustrates the torque waveform obtained from the torque sensor. The signal is divided into 2 phases regarding the amount of inserted load: load 1 with 1 kg. mass (green box) and load 2 with 2 kg. mass (red box). The estimation results were evaluated by using the RMSE and R-value methods [22], [23]. R-value is applied to determine the linear correlation coefficient between the measurement data and the estimation data to indicate the variance. Root Mean Square Error is applied to validate the result of the measurement data and estimation data, which approach to 0 is superior.

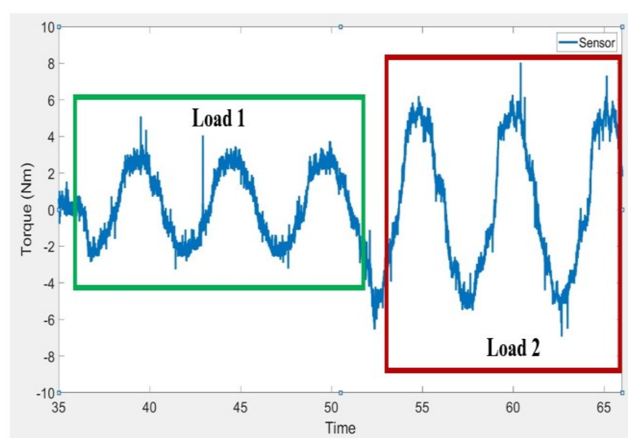
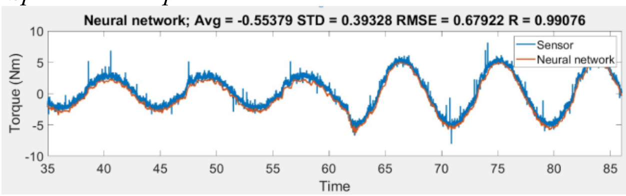


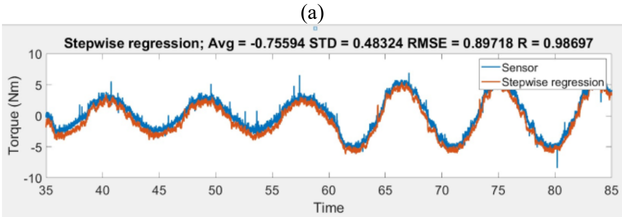
Fig.5 Result of Torque from physical sensor

C. Continuous torque measurement results

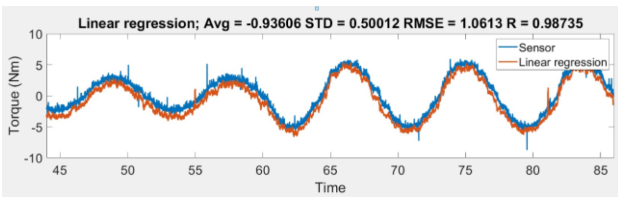
- Speed at 700 rpm



(a)



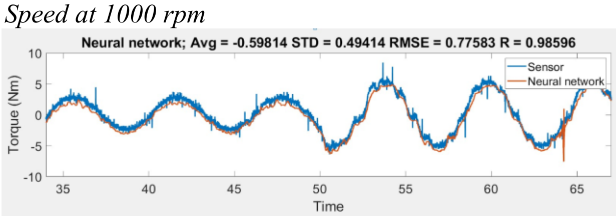
(b)



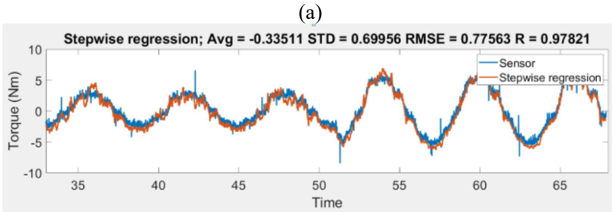
(c)

Fig.6 The comparison of torque estimation and error at 700 rpm (a)The Result of Neural Networks (b) Result of Stepwise regression (c) Result of Linear regression

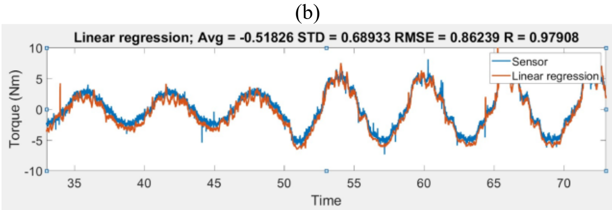
- Speed at 1000 rpm



(a)



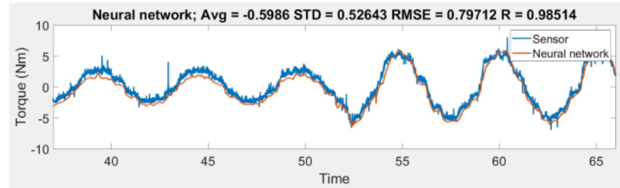
(b)



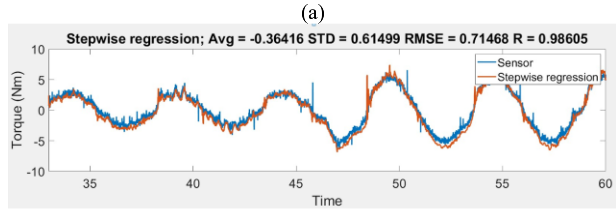
(c)

Fig. 7 Fig.7 The comparison of torque estimation and error at 1000 rpm (a) The Result of Neural Networks (b Result of Stepwise regression (c) Result of Linear regression

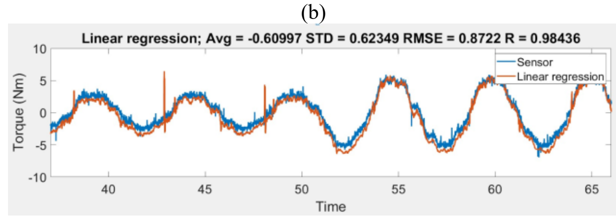
- Speed at 1200 rpm



(a)



(b)



(c)

Fig.8 The comparison of torque estimation and error at 1200 rpm (a)The Result of Neural Networks (b) Result of Stepwise regression (c) Result of Linear regression

Fig.6 (a), (b), and (c), depict the results of continuous torque measurement using generated torque estimation models of three selected machine learning models compared with actual torque from the sensor at 700 rpm. The performance of the estimation models was evaluated by RMSE and R values. Neural Networks performed with lowest estimation error at RMSE value of 0.6792 while Stepwise regression and Linear resulted with RMSE of 0.8971 and 1.0613 respectively.

Fig.7 (a), (b), and (c), depict the results of continuous torque measurement using generated torque estimation models of three selected machine learning models compared with actual torque from the sensor at 1000 rpm. The performance of the estimation models was evaluated by RMSE and R values. Stepwise regression performed with lowest estimation error at RMSE value of 0.7756 while Neural Networks and Linear resulted with RMSE of 0.7758 and 0.8624 respectively.

Fig.8 (a), (b), and (c), depict the results of continuous torque measurement using generated torque estimation models of three selected machine learning models compared with actual torque from the sensor at 1200 rpm. The performance of the estimation models was evaluated by RMSE and R values. Stepwise regression performed with lowest estimation error at RMSE value of 0.7147 while Neural Networks and Linear resulted with RMSE of 0.7971 and 0.8722 respectively.

TABLE 1 COMPARE THE RESULTS OF EACH METHODS

Models	700 rpm		1000 rpm		1200 rpm		T est. (ms)*
	RMSE	R value	RMSE	R value	RMSE	R value	
NNs	**0.6792**	**0.9908**	0.7758	**0.9860**	0.7971	0.9851	3.5
SR	0.8971	0.9870	**0.7756**	0.9782	**0.7147**	**0.9861**	1.35
LS	1.0613	0.9874	0.8624	0.9791	0.8722	0.9844	1.35

*T est. is Average of time estimation.

Table 1 summarizes the results of continuous torque measurement experiments. The Neural Networks based estimator performed well at low speed ranges (700 RPM and 1000 RPM) while consuming the highest resource among the others resulted in longest processing time for each estimation. Stepwise regression and Linear regression based estimated torque with more error compared to NNs at 700 RPM whereas Stepwise regression performed with lowest error at 1200RPM in both R and RMS measures. The estimation time of both methods was 1.35ms which is faster than the NNs based estimator due to their lower model complexity. It should be noted that NNs based estimator has worst performance at 1200RPM which may resulted from the delay in each estimation period as it consumes more resource.

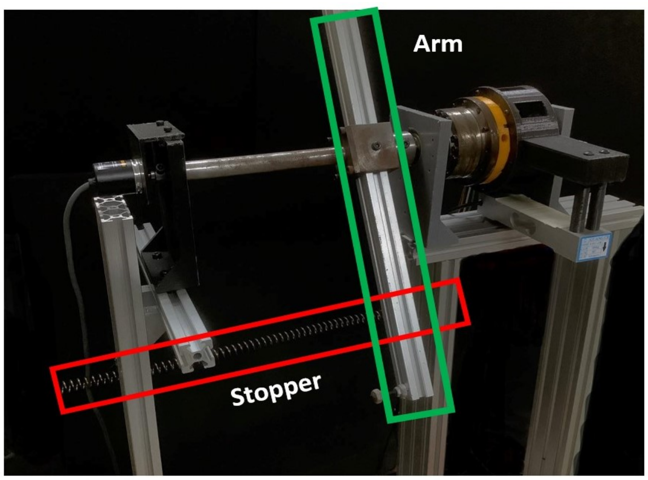


Fig. 9 Simulation of the operate of the robot arm when it collides

D. Simulated robotic arm collision detection

In this experiment, the motor testbench was configured to operate in different conditions to the previous one. The purpose of this experiment is to determine the response characteristic of torque detection employing generated torque estimation models which is crucial for safety required applications such as a robotic arm. The output shaft of the motor was attached to the arm without load. A spring based stopper was installed to block the arm's full cycle rotation as shown in Fig.9. This setting simulates an event of a robotic arm colliding with an object. The controller was programmed to limit the torque at a defined value by stopping the motor when the estimated torque is equal or larger. This experiment used the torque estimation models generated from the continuous torque measurement experiment. The limited torque values defined at 5 Nm. and 8 Nm.

E. Simulated robotic arm collision detection Results

Table 2 and Table 3 summarize the results of simulated robotic arm collision detection experiments. All estimation methods exhibit capability of detecting the amount of torque applied at the motor in a simulated use case with acceptable performance. However, at higher torque amount, the performance decreased in all estimation methods, especially at high speed ranges. The results from NNs based estimator were minor in most cases, suggesting that may be caused by the long estimation time in a limited resource processor. Despite the lowest model complexity, Linear regression outperformed in most experiment conditions which may result from a shorter time to take action as its estimation time is shortest. Thus, for the real-time required application, the lower model complexity should be considered.

TABLE 2 SIMULATED ROBOTIC ARM COLLISION DETECTION AT SPECIFIC TORQUE EQUAL 5 NM.

Motor speed	Model	Detected torque (estimator) (Nm)	|Error| (Nm) / % error reading
700 rpm	NNs	5.03	0.42 / 7.71%
	SR	5.23	0.18 / 3.56%
	LR	**5.18**	**0.16 / 3.00%**
1000 rpm	NNs	**5.12**	**0.48 / 8.57%**
	SR	5.17	0.55 / 9.62%
	LR	5.13	0.63 / 10.94%
1200 rpm	NNs	5.03	1.45 / 22.38%
	SR	5.03	1.21 / 19.39%
	LR	**5.04**	**0.28 / 5.26%**

TABLE 3 SIMULATED ROBOTIC ARM COLLISION DETECTION AT SPECIFIC TORQUE EQUAL 8 NM.

Motor speed	Model	Detected torque (estimator) (Nm)	|Error| (Nm) / % error reading
700 rpm	NNs	8.09	1.79 / 18.12%
	SR	**8.05**	**0.95 / 10.56%**
	LR	8.4	1.1 / 11.58%
1000 rpm	NNs	8.19	2.31 / 22.00%
	SR	8.07	1.3 / 13.87%
	LR	**8.08**	**0.89 / 9.92%**
1200 rpm	NNs	8.55	1.65 / 16.18%
	SR	8.18	1.27 / 13.44%
	LR	**8.08**	2.31 **3.69%**

TABLE 4 SPECIFICATION OF MOTOR

Motor parameter	Value	Unit
Motor	PMSM	-
Pole pair	8	-
Rated speed	4840	rpm
Stator resistance	0.43	Ω
Stator inductance	0.00014	H
Rated voltage	24	V
Rated torque	0.13	Nm
Gear ratio (Harmonic gear)	100:1	-

IV. Conclusion

A machine learning based PMSM torque estimation using the back-EMF signal has been presented in this paper. The proposed estimation model generation architecture has been implemented and incorporated with a motor testbench to facilitate the model training and data collection process. The estimation process was executed on a real-time embedded processor. The torque estimation was based on a choice of three statistical learning regression models including Linear regression, Stepwise regression, and Neural Networks for regression. The generated models form the proposed model creation system showed the capability of determining torque applied at the motor rotor where NNs achieved lowest estimation error at RMSE of 0.6792 while consuming the most resource. A simulated use case of the proposed torque estimation system has been studied in the robotic arm torque detection experiment to observe the ability to utilizing the generated model in real application. The proposed torque estimation method can be used for torque detection application with the maximum detection error of 22.38% where the majority of the results was below 10%. In future, we will investigate the other machine learning algorithms to be included in the proposed model generation process. Also, the improvement in performance and resource consumption are the goals to realize the proposed method in real-time applications.

References

[1] A. V. Dowling, O. Barzilay, Y. Lombrozo and A. Wolf, "An adaptive home-use robotic rehabilitation system for the upper body," in IEEE Journal of Translational Engineering in Health and Medicine, vol. 2, pp. 1-10, 2014, Art no. 2100310, doi: 10.1109/JTEHM.2014.2314097.

[2] J. W. Park, S. H. Hwang, and J. M. Kim, “Sensorless control of brushless DC motors with torque constant estimation for home appliances,” IEEE Trans. Ind. Appl., vol. 48, no. 2, pp. 677–684, 2012

[3] K. Nizamis et al., "Transferrable Expertise From Bionic Arms to Robotic Exoskeletons: Perspectives for Stroke and Duchenne Muscular Dystrophy," in IEEE Transactions on Medical Robotics and Bionics, vol. 1, no. 2, pp. 88-96, May 2019, doi: 10.1109/TMRB.2019.2912453.

[4] G. S. Gupta, S. C. Mukhopadhyay, C. H. Messom and S. N. Demidenko, "Master–Slave Control of a Teleoperated Anthropomorphic Robotic Arm With Gripping Force Sensing," in IEEE Transactions on Instrumentation and Measurement, vol. 55, no. 6, pp. 2136-2145, Dec. 2006, doi: 10.1109/TIM.2006.884393.

[5] T. Wildi, Electrical Machines, Drives, and Power Systems, Pearson New International Edition, England

[6] Gamazo-Real, J. C., Vázquez-Sánchez, E., and Gómez-Gil, J. (2010), “Position and speed control of brushless dc motors using sensorless techniques and application trends”, Sensors, 10(7), 6901–6947.

[7] M. Babaei, R. Asgharei, and A. Ahmarinejad, “Electromagnetic Torque and Speed Estimators for Permanent Magnet Synchronous Motor Drive Systems,” Energy Procedia, vol. 100, pp. 291–296, 2016.

[8] J. Choi, K. Nam, A. A. Bobtsov and R. Ortega, "Sensorless Control of IPMSM Based on Regression Model," in IEEE Transactions on Power Electronics, vol. 34, no. 9, pp. 9191-9201, Sept. 2019, doi: 10.1109/TPEL.2018.2883303.

[9] D. A. Morales, K. Findlater, and V. Chandran, “A motor controller using field oriented control and Hall effect rotor position sensors: Simulation and implementation,” EDERC 2014 - Proc. 6th Eur. Embed. Des. Educ. Res. Conf., pp. 235–239, 2014

[10] N. Wannadear and T. Kittikhun, “PMSM Torque Estimation Based on Machine Learning Techniques”, 2020 International Conference on Power, Energy and Innovations (ICPEI 2020), pp.137-140.

[11] Haykin, S. (2008), Neural Networks and Learning Machines, Pearson Prentice Hall, New Jersey, USA, (Vol. 3).

[12] X. Gang Su, “Linear regression analysis: Theory and computing”, World Scientific Publishing Co., 2009.

[13] NCSS, & LLC. (n.d.), “Stepwise Regression”, https://ncss-wpengine.netdna-ssl.com/wpcontent/themes/ncss/pdf/Procedures/NCSS/Stepwise_Regression.pdf.

[14] Boussaada, Z.; Curea, O.; Remaci, A.; Camblong, H.; Mrabet Bellaaj, N, “A Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for the Prediction of the Daily Direct Solar Radiation”, Energies 2018, 11, 620.

[15] Wei Tong. Mechanical Design of Electric Motors, CRC Press, Radford, Virginia,(2014).

[16] “LAUNCHXL-F28069M C2000 Piccolo MCU F28069M LaunchPadTM development kit | TI.com”, https://www.ti.com/tool/LAUNCHXL-F28069M?jktype=tools_software (accessed Feb. 24, 2020).

[17] “BOOSTXL-DRV8305EVM DRV8305N 3-Phase Motor Drive BoosterPack Evaluation Module | TI.com”, https://www.ti.com/tool/BOOSTXL-DRV8305EVM?jktype=tools_software (accessed Feb. 24, 2020).

[18] MathWorks, “Regression Learner App”, https://www.mathworks.com/help/stats/regression-learner-app.html.

[19] MathWorks, “Shallow Neural Network Time-Series Prediction and Modeling”, https://www.mathworks.com/help/deeplearning/gs/neural-network-time-series-prediction-and-modeling.html.

[20] MathWorks, “TI C2000 Support from Embedded Coder”, https://www.mathworks.com/hardware-support/ti-c2000.html.

[21] Liu, Y., Zhu, Z. Q., & Howe, D. (2006), “Instantaneous torque estimation in sensorless direct-torque-controlled brushless DC motors”, IEEE Transactions on Industry Applications, 42(5), 1275–1283.

[22] N. S. Hanspal, B. A. Allison, L. Deka, and D. B. Das, “Artificial neural network (ANN) modeling of dynamic effects on two-phase flow in homogenous porous media”, J. Hydroinformatics, vol. 15, no. 2, pp. 540–554, 2013.

[23] N.Wannadear, A Development of a Torque Estimation Process for Brushless Motors with Sensorless Techniques, Prince of Songkla University, Songkhla, Thailand.